

# Estimating secondary forest structure through the integration of remote sensing and modelling



**MSc Thesis by Julie Melling**  
**Sustainable Development: Track- Land-use, Environment and Biodiversity**  
**Utrecht University**  
**October 2010**



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Course Code: GEO4-2321

Course ECTS: 45

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## **Abstract**

The growth of secondary forest (SF) on former pastures has recently become an important topic of research in Neo-tropical regions as their role in carbon sequestration is proving to be important. In spite of the importance of secondary forests, monitoring and estimation of their growth has proven to be difficult as there is a lack of permanent sampling plots. As a result, most published forest growth models have been developed for primary and managed forests. The advancement of remote sensing technology, such as high spatial resolution space-borne images, has greatly aided the field of forest growth modelling and monitoring where ground-based data are rare. Remote sensing techniques are increasingly being integrated with forest growth models in an effort to monitor and project future tropical forest yields and carbon stocks. These studies have tended to focus on the effects of changing land-use on biomass accumulation instead of forest structure and have used airborne sensors rather than satellite imagery. It is the aim of this paper to integrate a secondary forest succession model which incorporates the effects of pasture management on tree size distribution of secondary forest in central Amazonas, with remotely sensed high spatial resolution images of that area. The algorithm, combined with the allometric equations, correctly estimated tree size distribution ( $\alpha$  0.01); however it under-estimated mean biomass and tree density by almost 70%. Although the algorithm and allometric equations accurately estimated biomass, the algorithm estimated mean tree crown width to be 3% smaller than field data estimates. The secondary forest growth model's simplification of plant species present in secondary forest led to the over-estimation of very small trees and thus a significant difference between the model and the algorithm. Future work should involve creating a biomass function that is more stratified to represent trees with different growth rates.

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## 1. Introduction

The deforestation of the Amazonian rainforest has been well documented (Fearnside, 1982; 1996). Logged areas are commonly converted to pastures (Buschbacher, 1986) but due to poor soil quality (Serrao, 1978) and lack of economic incentives, these areas are often left fallow or abandoned after a number of years allowing for secondary forests to grow (Feldpausch *et al*, 2004). The rate of growth of secondary forest on these abandoned pastures can be surprisingly high, with above ground biomass accrual reaching as much as 25% of mature forest biomass levels after only eight years (Uhl *et al*, 1988). Therefore, the growth of secondary forest in these former pastures has recently become an important topic of research as their role in carbon sequestration is proving to be important (Feldpausch *et al*, 2004).

The intensity of previous land-use is an important factor affecting secondary forest growth (Uhl *et al*, 1988). It has been found that the rate of forest re-growth is inversely proportional to the intensity of land-use e.g. length of time under pasture, frequency of burning, etc. (Nepstad *et al* 1991; Uhl *et al*, 1988). Previous land-use intensity also affects the structure of the subsequent secondary forest (Gehring, 2005; Steininger, 2000). Gehring (2005) showed that while a moderate increase in land-use intensity had little effect on biomass accumulation, it profoundly changed the structure of the secondary forest, with a shift from a closed canopy forest with little understory growth to an open canopy with more shrubs and grasses. This development of gaps in the canopy can result in a more fire prone, degraded ecosystem (Gehring, 2005).

In spite of the importance of secondary forests, monitoring and estimation of their growth has proven to be a difficult task as sample plots are often very small, sparsely distributed and bias due to accessibility limitations (Clarke *et al*, 2004). As a result of these limitations, sufficient times-series for secondary forest growth models are rare (Vanclay, 1994). Therefore, most published forest growth models have been developed for primary and managed forests (Alder, 1980; Alder & Silva, 2000; Keller *et al*, 2004).

Neef & dos Santos (2005) developed a tropical secondary forest growth model using a chronosequence but the model variables were independent from prior land-use and did not model forest structure. A dynamic, spatial growth model of tropical secondary forests developed by Rebel *et al* (2001) simulated the effects of previous land-use intensity (burning frequency and grazing intensity) on tropical secondary forest growth. They found that while biomass accrual rates were reduced with increasing land-use intensity, the model also showed a significant change in secondary forest composition with structure and tree size distribution shifting towards a forest which consists of more grasses and weeds and less large trees.

The advancement of remote sensing technology, such as the advent of high spatial resolution

space-borne images has greatly aided the field of forest growth modelling and monitoring where ground-based data are rare (Frolking *et al.* 2009). High resolution imagery makes it possible to measure individual tree crown diameters and areas from a space-born vantage point. These observations can be directly and indirectly comparable to ground based measurements such stem diameter at breast height (dbh) and biomass. New satellites such as IKONOS can therefore provide measurement over a spatial extent otherwise unachievable in field and forest research (Franklin *et al.*, 2001, Clark *et al.* 2004)

Much research has focused on forests with low species diversity and regular geometric crown shapes (e.g. temperate coniferous forests) as these images allow for easier crown detection (e.g. Fakjiwsju *et al.*, 2006). Tropical forests on the other hand have high species diversity and therefore a wide range of crown shapes which can cause problems in automated tree crown detection (Palace *et al.*, 2008). Still, remote sensing techniques to differentiate trees differing in structure appear to have potential (Broadbent *et al.* 2008).

IKONOS images have been used extensively in the Large-scale biosphere-atmosphere in Amazonia (LBA) experiment for enhancing studies of fine-scale heterogeneity in vegetation and land-use change (Hurt *et al.*, 2003). These images provide data for remote regions and have been used to estimate, among others, tree density and tree crown widths (Asner *et al.* 2002; Palace *et al.*, 2008). Individual tree biomass estimates can then be derived from these estimates using allometric equations (Keller *et al.*, 2001). Asner *et al.* (2002), manually derived tree crown diameter estimates from IKONOS images but found that manual derivations of tree crowns over large images is labour intensive and often inconsistent (Asner *et al.*, 2002). Automated routines are proving to be more successful at estimating tree crown areas. Palace *et al.* (2008) analysed a high resolution IKONOS image with an automated crown delineation algorithm for primary tropical forests. While high resolution satellite images are increasingly being used for biomass estimation of tropical forests, no published articles were found on using them to estimate tree crown number or size in neo-tropical secondary forests.

Remote sensing techniques are increasingly being integrated with forest growth models in an effort to monitor and project future tropical forest yields and carbon stocks. These studies have tended to focus on the effects of changing land-use on biomass accumulation instead of forest structure and have used airborne sensors rather than satellite imagery (e.g. Neeff *et al.*, 2005).

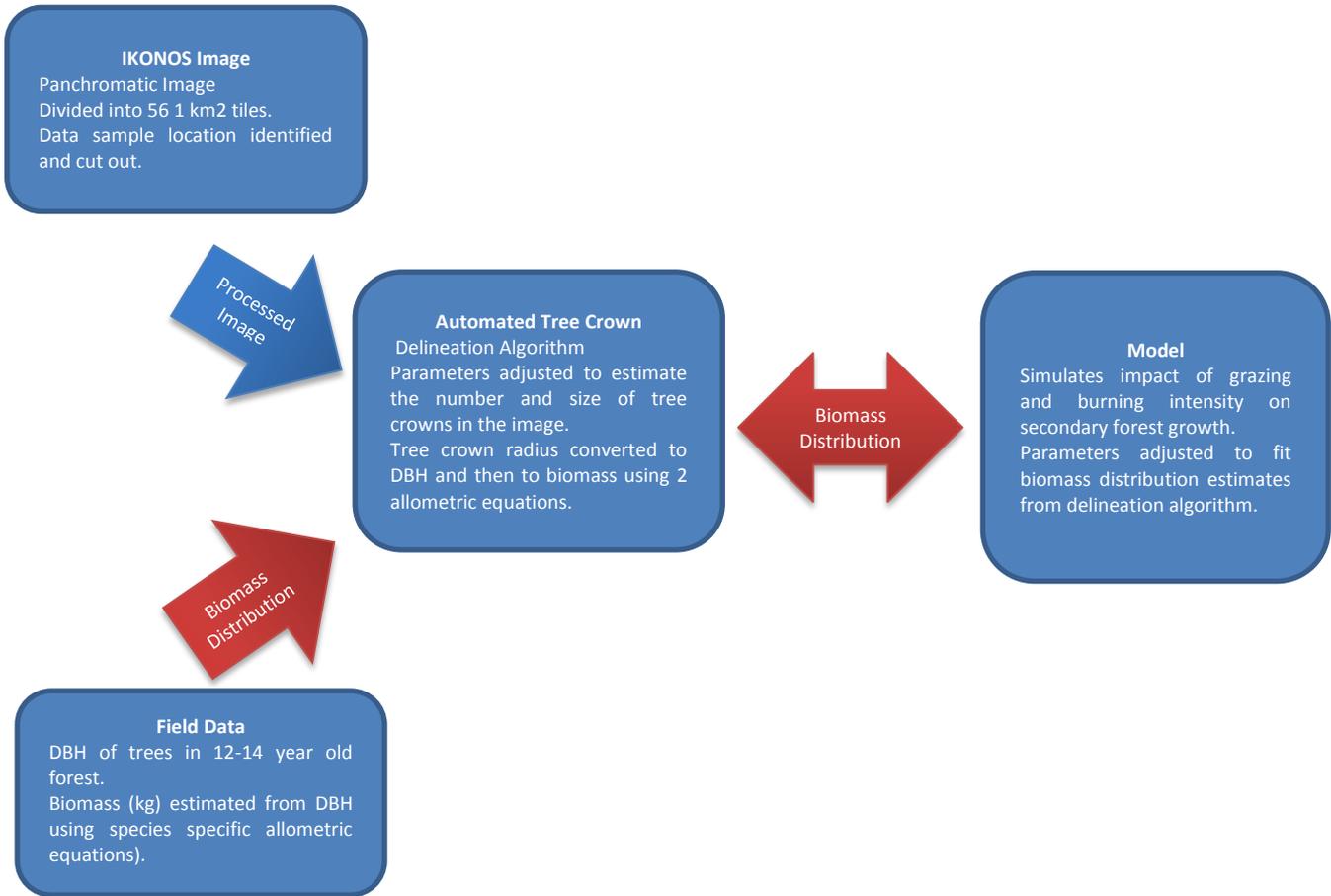
It is the aim of this paper to integrate a secondary forest succession model (Rebel *et al.*, 2002) which incorporates the effects of pasture management on tree size distribution of secondary forest in central Amazonas, with remotely sensed high spatial resolution images of that area (Palace *et al.* 2008). The results will provide insight into how previous land-use intensity affects secondary forest structure.

## **1.1 Hypothesis**

- a) High-resolution IKONOS images used in conjunction with a tree-crown delineation algorithm can be used to delineate secondary forest tree crown diameters. Based on the relationship between crown diameter and field-measured tree diameter and aboveground biomass, IKONOS-based delineated tree crowns can be used to estimate tree size distribution (TSD) of secondary forests in the Manaus region, Amazonas.
- b) Remotely sensed high spatial resolution images of Amazonas secondary forest can be used to calibrate a growth model that simulates the effects of previous land-use intensity on tree size distribution of Amazonian secondary forests (Rebel *et al*, 2002). There will be no significant differences between TSD results from the model, those estimated using the remotely sensed images and those measured in the field

## **2. Methods**

Figure 1 shows an overview of the study methods. An automated tree crown delineation algorithm developed by Palace *et al*, (2008) was calibrated to estimate tree crown numbers and size. This was done on a 1 m resolution panchromatic IKONOS image of secondary forest north of Manaus, Brazil. Biomass cannot be directly calculated from tree crown size. Consequently, allometric equations were used to convert crown radius to diameter at breast height (dbh; 1.3m) (T.R. Feldpausch, *personal correspondence*) and then to biomass using a mixed species biomass equation developed for pioneering tropical forest species (Nelson *et al*, 1999). The algorithm was calibrated using dbh field data of secondary forests of the same area (Feldpausch *et al*, 2004). In order to calibrate the secondary forest growth model, the biomass distribution estimates from the algorithm were then compared to biomass distribution results of the model.



**Figure 1. Overview of methods.**

## 2.1 Area



**Figure 2. Location of study area, Embrapa District of Suframa (Das) research site north of the city of Manaus in the Brazilian state of Amazonas.**

The study area is located in Amazonas, Brazil, ~ 53km north of the city Manaus ( $2^{\circ}34' S$ ,  $60^{\circ}02' W$ ) (Fig 2). It is predominantly covered with old growth, closed canopy, dense, evergreen forest, although there are many pockets of grassland where the primary forest was cleared in the 1980s and seeded with grass to be used as pasture for cattle. Many of these pastures are in some state of decline or completely abandoned altogether. Secondary forests have been replacing these abandoned pastures resulting in a patchwork of different aged forests in the area (Feldpausch *et al*, 2004).

## 2.2 Field Data

Field data of secondary forest sites was taken from a study on Carbon and nutrient accumulation in Secondary Forests in Amazonia (Feldpausch *et al*, 2004). This data was sampled in 2001. The diameter at breast height (dbh) was measured for all live trees from a 12-14 year old secondary forest site within the Brazilian Agency for Agricultural Research Agricultural District of SURFAMA (Das) pasture research site. A total of 235 trees were measured within 4 plots that totalled an area of  $420m^2$ . The pasture site represented typical management intensity for the area i.e. light to moderate grazing of less than 10 years. The sample sites were part of a mixed secondary forest that was dominated by species from the genera *Vismia* with *Bellucia*, *Glabora*, *Laetia* and *Cecropia*, also present. Feldpausch *et al* (2004) used species specific allometric equations to

convert dbh to biomass for the dominant tree species in the plot and a mixed-species equation for all others. This mixed-species equation was used to convert dbh to biomass for this study also (discussed further below). Table 1 shows an overview of the genera sampled at the site.

<b>Genus</b>	<b>Average Biomass</b>	<b>No. of Individuals</b>
<i>Vismia</i>	28.49	104
<i>Laetia</i>	14.19	24
<i>Bellucia</i>	30.74	17
<i>Goupia</i>	31.38	14
<i>Cecropia</i>	188.96	4
Indet	1.89	69

**Table 1. Tree genera sampled at DAS 3 sample site with average tree biomass, number of individuals of each genera. Indet represents unidentified species.**

### **2.3 Satellite Image**

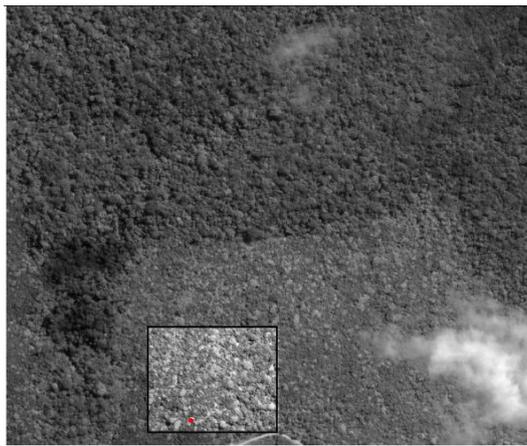
A 56 km<sup>2</sup>, 1m resolution, panchromatic IKONOS image (Space Imaging Inc. Thorton, CO, USA) of the study area, taken on 20/06/2001, was used (fig 2a). The image was first divided into 1 km<sup>2</sup> tiles. The sample site of the 12-14 year old secondary forest (fig 2a) was then located on one of the tiles. An sub-plot of 5.22ha was cut out around the sample site (fig 2b). This ‘sub-image’ was used to calibrate the algorithm. Data for only one 12-14 year old forest in the image was available; therefore validation of the algorithm was not possible i.e. the algorithm could not be tested against a second image of 12-14 year old neotropical forest in order to provide an acceptable level of confidence that it could accurately delineate tree crowns. Instead, additional sub-plot of different sizes - 1.02ha, 2.1ha 4.08 ha- around sample area were cut out in Erdas Imagine and used as validation images (fig 3c-e). As the algorithm creates a border (discussed below) of 10 m around the image the actual areas analysed were 0.64ha, 1.7ha, 3.35ha and 4.37ha respectively.

a)



b)

c)



d)

e)

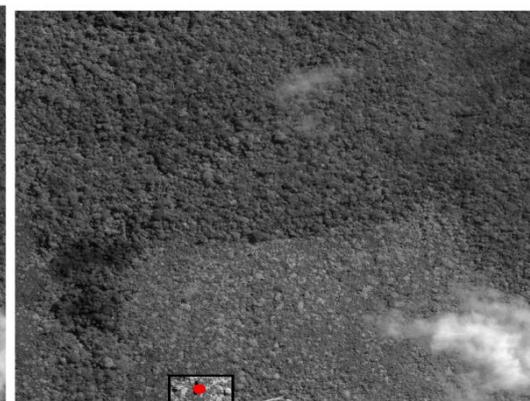


Figure 3a. 56km<sup>2</sup> IKONOS image of study area with 1km<sup>2</sup> tile with 12-14 year old secondary forest sample site highlighted. Image taken June 2001. b-e 1km<sup>2</sup> tile of IKONOS image with sub-plot areas around sample site, b) 5.22ha, c) 4.08ha, d) 2.1ha and e) 1.02ha. Red dot shows location of field sample site.

## **2.4 Crown Delineation Algorithm**

The automated crown delineation algorithm used in this study was developed by *Palace et al* (2008). It is based on a spatial analysis of the brightness patterns in an image and combines two commonly used crown delineation processes; a) local maximum filtering - finding the brightest pixels in the image and using them to 'seed' tree crowns. This process assumes that the top of the crown is at its centre and is also the highest and therefore brightest point, b) local minima value-finding – using the darkest pixels to create edges of tree crowns - this process assumes that the tree crown edges are much lower and therefore darker than the centre of the crown and that gaps between trees are also very dark. It uses three concepts: repeated local maximum filtering, user-defined thresholds that terminate tree crown analysis, and the removal of previously analysed pixels from further analysis (*Palace et al*, 2008).

Before the algorithm can delineate tree crowns, two pre-processing steps must be performed. The image is first smoothed using an adjustable window that moves across the image and calculates the average value of each pixel and its adjacent neighbours. By doing this, information is retained on a 1 x 1 pixel resolution while reducing noise in the image. Next the modal brightness value of the image is found. It was found by *Palace et al* (2008) that the smallest local maximum value was nearly equal to the modal brightness value for the entire image therefore, this value is used to limit the local maximum value for seeding of tree crowns.

The algorithm assumes that the top of the tree crown is circular and rounded and therefore is the most illuminated part with the brightest pixel value. The algorithm first searches the image for the brightest value and sets crown centres at these local brightness maxima (crown seeding). Next, transects are run in 360 directions from each maximum. This process is repeated for the next brightest value and continues in this manner until the local maximum reaches the modal brightness value of the image.

Each ordinal transect is terminated when one of 2 user-defined derivative thresholds are met: a) the drop and b) the rise. These thresholds are based on the assumption that tree crowns are rounded and therefore the brightness value of each pixel decreases with increasing distance from the crown top until the tree crown edge is met. At this point it is assumed that the gaps between trees have the lowest brightness values.

- The drop is the maximum difference between the crown seed (local brightness maxima) and current pixel. Sudden drops in brightness are detected, which represent the shadow effect created when the slope of the crown increases dramatically. This threshold is a new concept in the algorithm.
- The rise is the maximum difference allowed between the two adjacent pixels along the

transect. It is used to detect small changes in brightness value of a pixel as the transect reaches the edge of a crown.

These thresholds are image dependent as the overall image brightness and contrast affects how the algorithm processes the local maxima.

The transect length is limited to 10 m as the field data dbh measurements converted to crown radii (using eq. 1 below) show that the 12-14 year old trees in the image do not have crowns with radii larger than this. A border 10 m is therefore around the edge of the image so that tree crowns do not run off the image. Tree crowns are approximated as circles around the local maxima with a radius that is half the length of the longest pair of opposing transects. Once a crown has been delineated the pixels within the crown are removed from further analysis. The assumption that tree crowns are circular can lead to inaccurate estimates of tree crown size, as transects can be terminated prematurely due to shadows or extend longer than the crown width when crowns are merged (Palace *et al*, 2008).

### **2.5 Algorithm Calibration**

The thresholds were tested for sensitivity and adjusted accordingly to delineate tree crowns in the 5.22ha sub-plot (fig 3b). A new secondary forest model to estimate above ground tree biomass directly from tree crown diameter was developed. First, tree crown size estimates were converted to dbh using the equation

$$\log(D) = \log(D_C) + (-0.3685)/0.6277 \quad \text{eq. (1)}$$

where  $D$  is diameter at breast height,  $D_C$  is crown diameter and log is the natural log (T.R. Feldpausch, *personal correspondence*).

The log of the  $D$  was then converted to biomass using a mixed species biomass equation (mentioned in section 2.2) (Feldpausch *et al*, 2004)

$$\text{Biomass} = 2^{(-1.9968 + 2.4128 * \log(D))} \quad \text{eq.(2)}$$

where  $D$  is diameter at breast height (Nelson *et al*, 1999).

Biomass distribution estimates from the above model (binned in 5kg classes) were then compared to field data. Goodness of fit was measured using root mean squared error (RMSE) of biomass distributions. Once the algorithm thresholds were fitted to the field data the algorithm was applied to the sub-images of different sizes in an effort to validate it (fig 3c-e).

### **2.6 The Secondary Forest Growth Model**

A spatial, dynamic model of secondary forest establishment (Rebel *et al*, 2002) was used to

estimate tree size distribution after land abandonment. Their model was developed to quantify the potential impact of pasture management practices on species composition, density, net primary productivity and biomass accumulation in abandoned pastures in the Central Amazon. It was created in PCRaster (PCRaster, 2009; VanDeursen, 1995; Wesseling *et al*, 1996) which is a high-level, dynamic, spatial modelling language and as such is very suitable for modelling ecological processes.

For simplicity's sake it is assumed that there are three plant types during succession: *Brachiaria* – grass, *Borreria* – weed, *Vismia* – tree. It uses a grid of 1m x 1m cells to constitute 1 hectare and a 2 month time-step. At each time-step a number of values are calculated for each grid cell including which plant species occupies it, the age of the species, the total biomass and net primary productivity. As the model is spatial, the distribution of these variables is also calculated for each time-step. For this study only the biomass distribution will be used to parameterise the model.

#### 2.6.1 Modelled plant characteristics and interactions

##### ***Brachiaria***

A *Brachiaria* plant has a lifespan of between 2 and 6.7 years. After 2 years the probability of death increases with age. It reproduces by spreading tillers to neighbouring empty cells. Its ability spread begins after 2 months, after which spreading is age dependant. The probability of spreading increased until 12 months and then it decreases again.

If the *Brachiaria* is grazed its age is reduced by 2 months. The chance of the plant being grazed is a function of its age and the grazing intensity. If grazing intensity is set to maximum then 70% of all 2 to 12 month old plants are grazed. Plants between 2 months and 2 years can be grazed with the probability of being grazed decreasing after 1 year.

Grazed plants between the ages of 2 and 6 months have a probability of being of being destroyed by the trampling of grazers. When this happens a patch is formed. This probability is a function of age and grazing pressure. Once a patch is formed it can be recolonized by *Brachiaria*, or colonized by the weed *Borreria* or the tree *Vismia*.

##### ***Borreria***

*Borreria* seeds can be spread up to 3m away from the plant in all directions. The probability of a cell recruiting a weed plant depends on the distance it is from the parent plant. Seeds can also be dispersed further with a much lower probability (transported by wind, animals). Only empty cells (patches) can be recruited. The weed can reproduce up to the age of 8 months. It cannot be grazed or trampled on but it does compete with the other plant species for a cell. It will always lose to a

*Vismia* sprout but the probability of a weed seed out-competing a grass tiller increases with the age of the grass. Weeds are killed by fire or shading from *Vismia*.

### ***Vismia***

*Vismia* has the longest life span (>20 years). It can send root sprouts to neighbour cells and will grow if it is empty. There is also a probability of a cell being recruited by a tree seed but only if the cell is already occupied *Borreria* older than 1 year. A tree can only be killed by self-thinning, a probability which occurs when the average tree biomass surrounding it is larger than its own for more than 40 months. A tree that is shaded accumulates only 10% of the biomass of the surrounding un-shaded trees.

#### **2.6.2 Parameterisation**

Sensitivity tests using the Monte Carlo method were performed on all the parameters of the model in a previous research project (Melling, 2009). Tree density was almost twice as sensitive to the probability of a patch being recolonized by the grass species than any other parameter. Other sensitive parameters included the probability of *Borreria* seed dispersal and the probability of *Borreria* dying by over-shading by *Vismia*. The parameterisation therefore focused on these parameters. Because the field data was taken from ranches with low intensity management regimes, the model was first set to the lowest burning and grazing intensities (no burning and 25% grazing). It was then run for 12 years with different values for all three parameters (0.01-0.09 for *Borreria* seeding and 0.1-0.9 for patch re-colonisation and *Borreria* death). The resulting tree biomass distributions were then compared to the field data and the algorithm estimates.

## **2.7 Statistical analysis**

### **2.7.1 Algorithm**

The field data consisted of 235 trees in an area of 420m<sup>2</sup>. This is much smaller than the IKONOS image area. Therefore, 235 tree crown measurements were randomly taken from the algorithm output in order to achieve a more accurate comparison to the field data. The tree biomass distribution of the algorithm estimates and the field data were first compared using the Kolmogorov-Smirnov two-sample test. This is a non-parametric test that investigates differences between two distributions. (Sokal & Rolff, 1995).

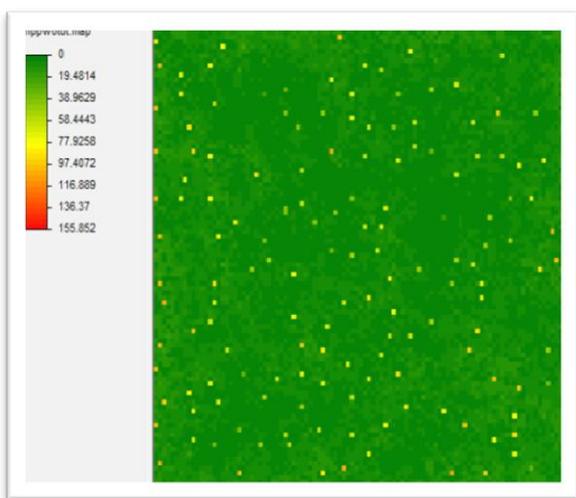
In order to get an insight into the findings, descriptive statistics for both the algorithm results and the field data were also calculated and compared. F-tests (Sokal & Rolff, 1995) were also performed on crown diameter, dbh and biomass of the algorithm results and field data to test for equal variances. T-tests to test for equal means were then performed on those results that had equal

variance. Welsh's approximate t-test of two samples was performed to test for equal means on samples with unequal variances (Sokal & Rolff, 1995).

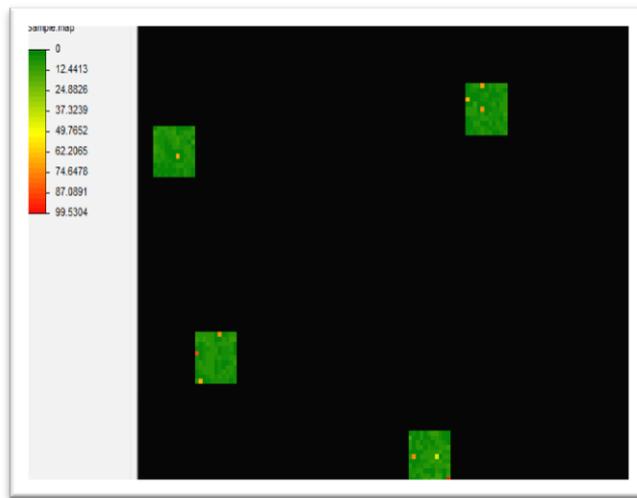
### 2.7.2 Model

The model produced a simulated biomass map that contained biomass values for every grid cell after 12 years in an area of 1ha (fig 4a). In order to create comparable sample sizes between the algorithm results and the model results, 4 sample areas of 100 m<sup>2</sup> each were taken from the biomass map (fig 4b). This was done in PCRaster using the “Resample” command. Clone maps of 100m<sup>2</sup> with specified x and y co-ordinates were first created. Using the resample command, PCRaster uses these clone maps to create sample plots based on the biomass map at specific coordinates.

Estimates of tree biomass distribution from the model were then compared to those developed from the IKONOS imagery using the Kolmogorov-Smirnov two-sample test (Sokal & Rolff, 1995). Descriptive statistics were also calculated for this sample and compared to the algorithm results.



**Figure 4a.** Example of a simulated biomass map from secondary forest growth model



**Figure 4b.** Example of a sample area of simulated biomass map from secondary forest growth model

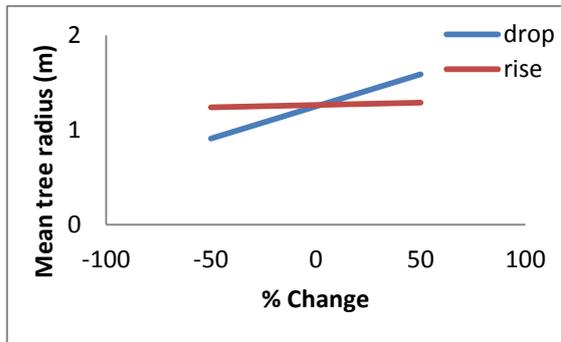
## **3. Results**

### 3.1 Algorithm calibration

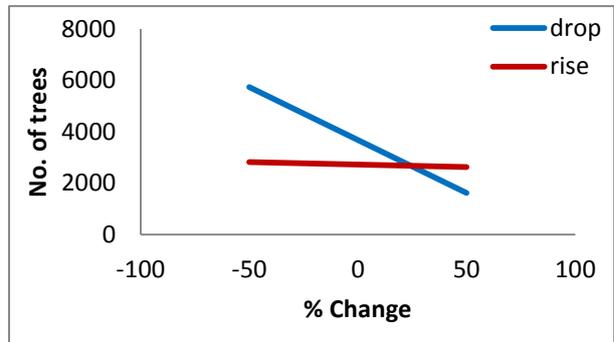
The sub-sampled sections of the IKONOS image used in this study were much smaller than those of the original calibration by Palace *et al* (2008) and consequently the algorithm was unable to delineate trees from images. It was found that disabling the pre-processing step of using the modal brightness value to limit the local maximum value and setting the this limit to 0.22 corrected this problem.

The sensitivity analysis showed that the mean tree crown radius and number of crowns were very sensitive to the drop while even a 50% change in the rise produced little change in either mean tree crown radius or number of trees counted. Figures 5a and 5b show that adjusting the thresholds (drop

and rise) changed the number and size of the tree crowns counted. Decreasing the rise and drop decreased the estimated tree crown size and increased number of trees detected. The sensitivity analysis also showed an inverse relationship between the mean tree crown radius and tree density.

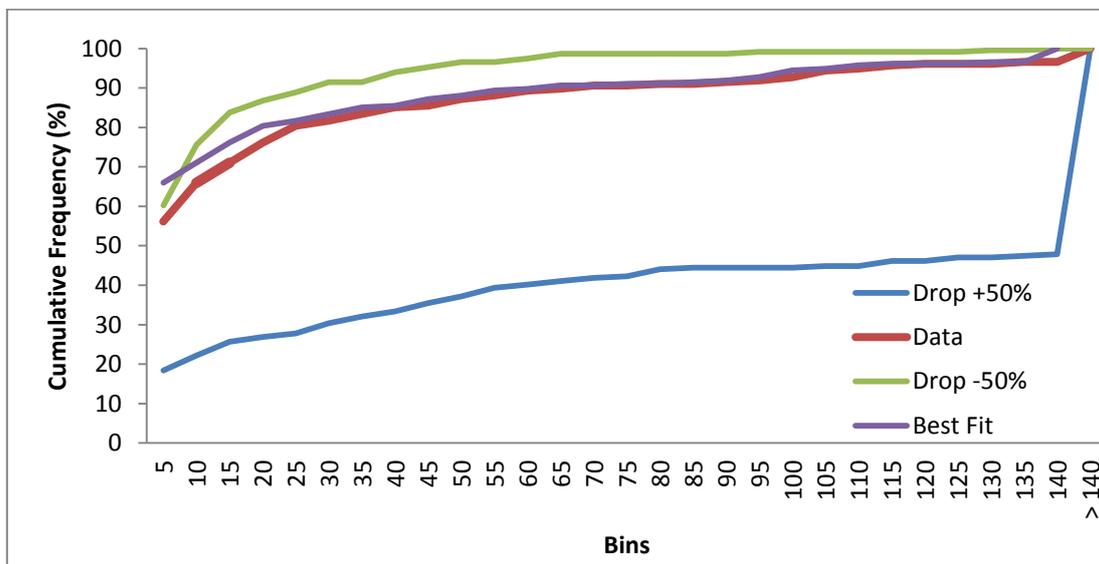


**Fig 5a. Sensitivity of mean tree crown radius to tree crown delineation algorithm thresholds drop and rise.**



**Fig 5b. Sensitivity total number of tree crowns counted to thresholds drop and rise of tree crown delineation algorithm.**

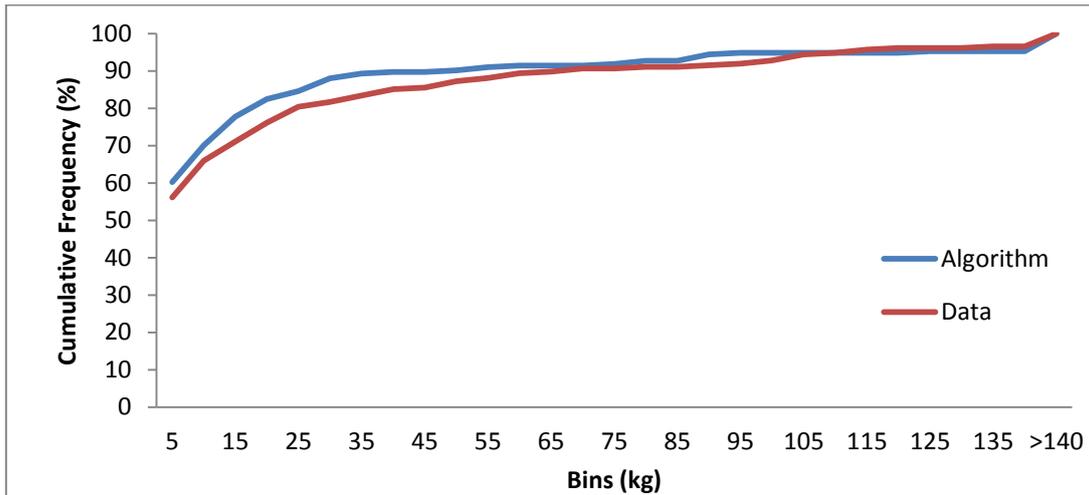
Further analysis focused on the drop as tree crown estimates were not very sensitive to the rise. When the effects of varying the drop were analysed (fig. 6) it could be seen that when it were too low the algorithm over-estimated the number of small trees and under-estimated the number of large trees. When the drop was too high there was an under-estimation of small trees and an over-estimation of large trees. The very sudden increase in the +50% line shows that most of the trees were over 140 kg.



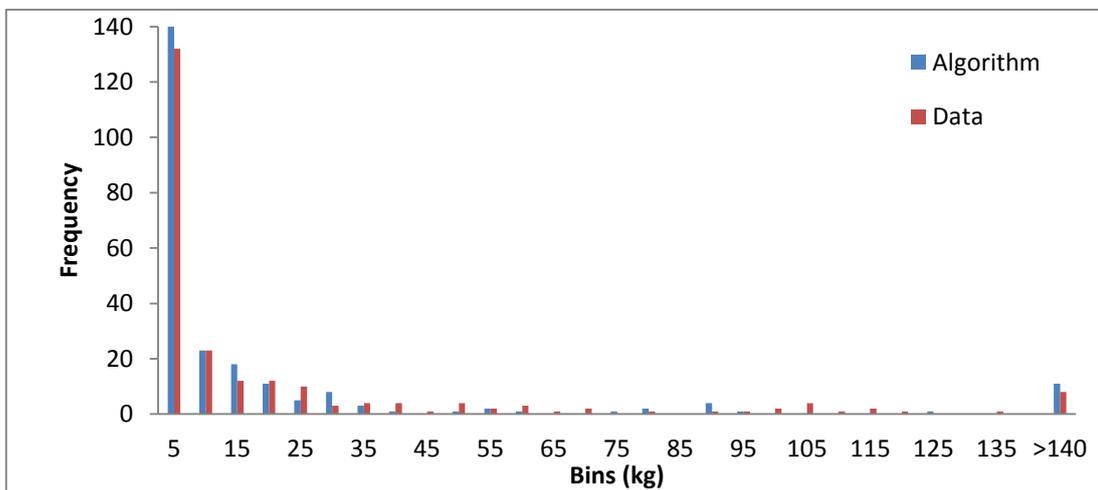
**Fig 6. Cumulative frequencies comparing biomass distribution of field data to tree crown delineation algorithm estimates when the Drop parameter is varied 50% above and below the best fit value.**

Using RMSE the best fit parameters were found to be 0.07 for the drop and 0.005 for the rise (fig 7a and b). The sharp increase at the end of the graph of figure 7a corresponds to the grouping of all

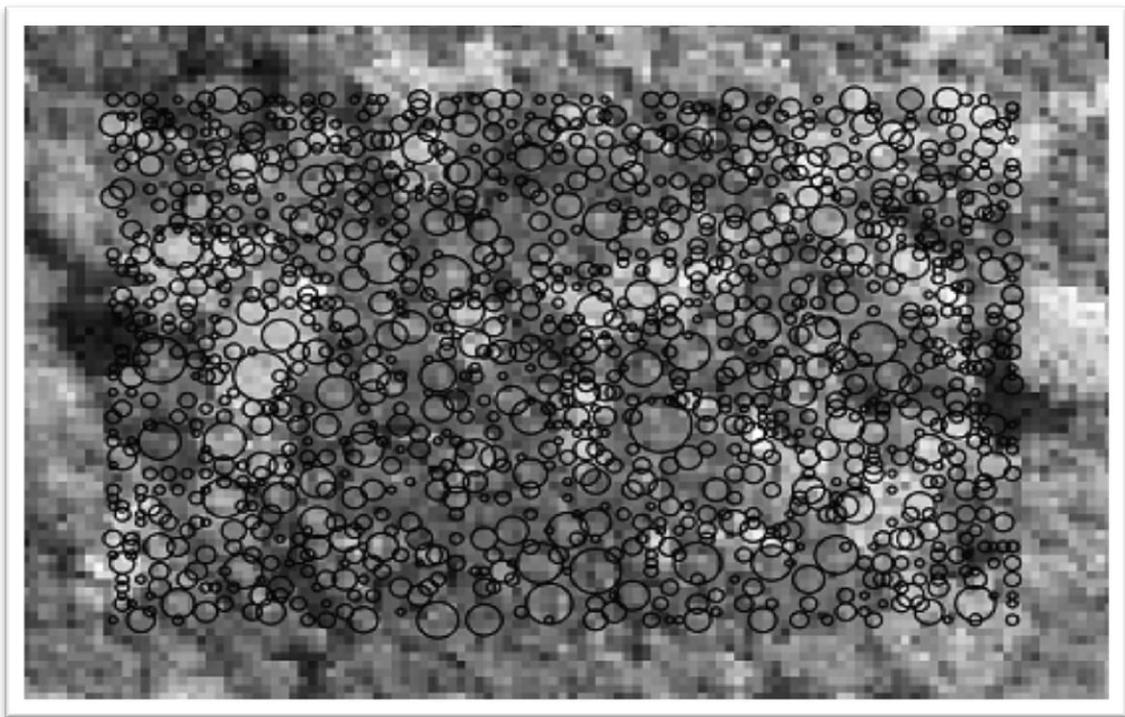
trees over 140kg in figure 7b. Figure 8 shows visual representation of the results.



**Figure 7a** Tree biomass cumulative frequencies of 12-14 year old neo-tropical secondary forest. Red represents field data from Das 3 sample site in Amazonas; blue represents automated tree crown delineation algorithm estimates



**Figure 7b** Tree biomass frequency distribution of 12-14 year old neo-tropical secondary forest. Red represents field data from Das 3 sample site in Amazonas; blue represents automated tree crown delineation algorithm estimates



**Figure 8. Output from automated tree crown delineation algorithm overlain on IKONOS image of 12-14 year old secondary forest in Amazonas, Brazil. Black circles represent crown edges.**

Estimates of the minimum, mean and maximum crown diameter, dbh and biomass can be seen in table 2. While mean tree crown diameters were slightly underestimated (3%) no significant differences ( $\alpha < 0.01$ ) were found between the algorithm output and the field data. Error propagation when converting the crown diameter to dbh resulted in a doubling of this under-estimation (6%). This error increased again to 16% when dbh was converted to biomass. It can also be seen that the maximum crown diameter was over-estimated by more than 1 meter. This led to a gross over-estimation of the maximum biomass. The algorithm under-estimated tree density by almost 70%.

	<b>Field Data</b>	<b>Algorithm</b>
<b>Crown Diameter(m)</b>		
Min	0.69	0.87
Mean	1.91	1.85
Max	5.68	6.88
St Dev	1.02	0.91
<b>DBH (cm)</b>		
Min	1.00	1.45
Mean	5.69	5.32
Max	28.65	38.88
St Dev	5.02	4.46
<b>Biomass(kg)</b>		
Min	0.13	0.33
Mean	22.24	18.54
Max	361.45	929.73
St Dev	46.74	49.17
<b>Density (tree/ha)</b>	5595	1728

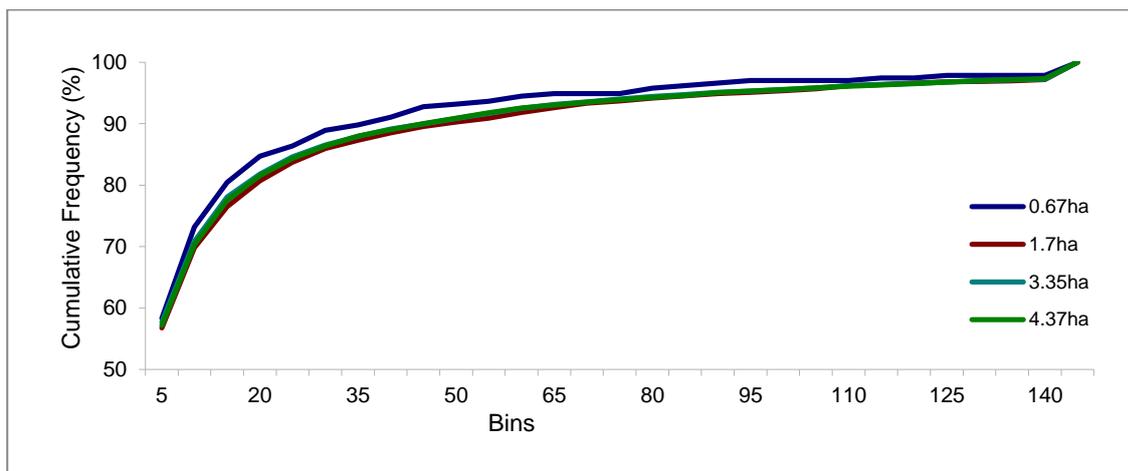
**Table 2. Descriptive statistics of crown diameter, dbh and biomass for automated tree crown delineation algorithm and field data estimates.**

### 3.2 Comparison different sized images

Table 3 shows descriptive statistics comparing the images of different size areas. Differences were found between the different image sizes even though they were of roughly the same location. The 1.7ha area had the largest estimated mean biomass and the lowest tree density, whereas the smallest image, 0.67ha, had the lowest estimated mean biomass and the largest tree density. No Significant difference ( $\alpha < 0.01$ ) was found between the mean biomass and tree density of the two larger images. The Kolmogorov-Smirnov two sample test showed no significant differences ( $\alpha < 0.01$ ) between the biomass distributions of any of the images (fig 9).

Statistic	0.67ha	1.7ha	3.35ha	4.37ha
<b>Biomass</b>				
Min	0.33	0.33	0.33	0.33
Mean	15.57	19.94	18.67	18.53
Max	854.23	982.73	929.73	929.73
<b>Density</b>	1855	1673	1752	1728

**Table 3. Descriptive statistics of biomass and tree density trees/ha estimates from the automated tree crown delineation algorithm for 4 different image areas around the field sample site**



**Figure 9. Cumulative frequencies comparing biomass distribution of tree crown delineation algorithm estimates for images of field data site, ranging in size from 0.67ha to 4.37ha.**

### 3.3 Model Parameterisation

The sensitivity analyses found that while mean biomass was most sensitive to patch recovery (fig 10a), tree density was most sensitive to the probability of *Borreria* death caused by over-shading (fig 10b). This contradicts previous findings of Melling (2009).

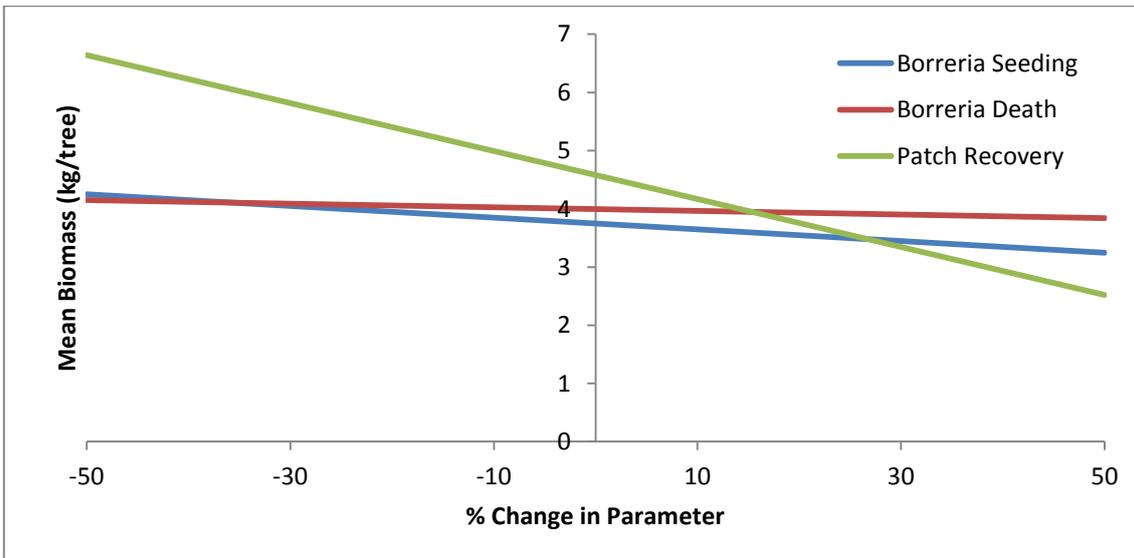


Figure 10a. Sensitivity of secondary forest growth model estimate of mean biomass to the parameters *Borreria* Seeding, *Borreria* Death and Patch Recovery.

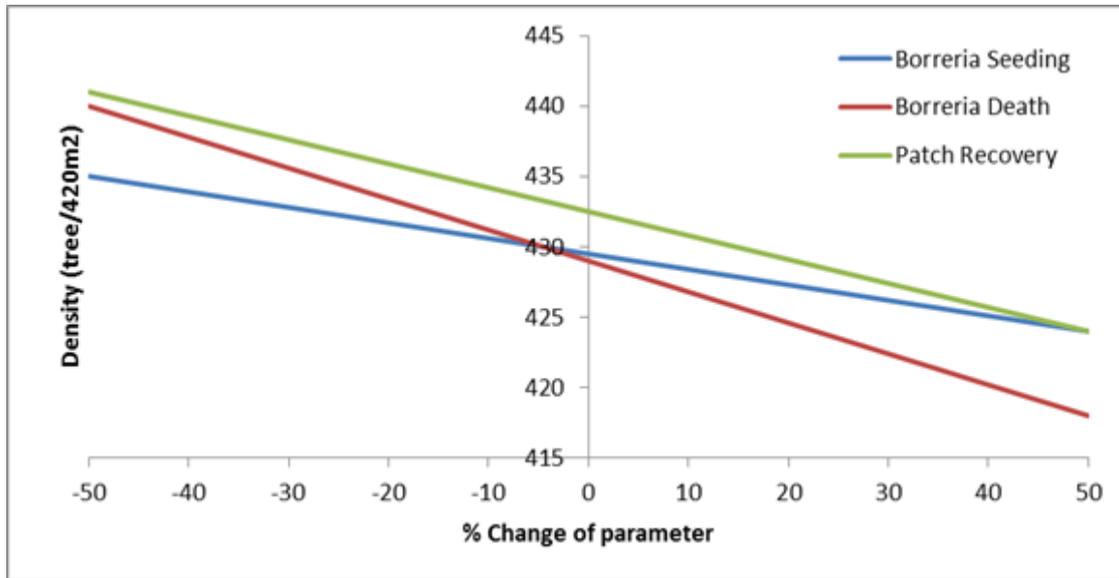
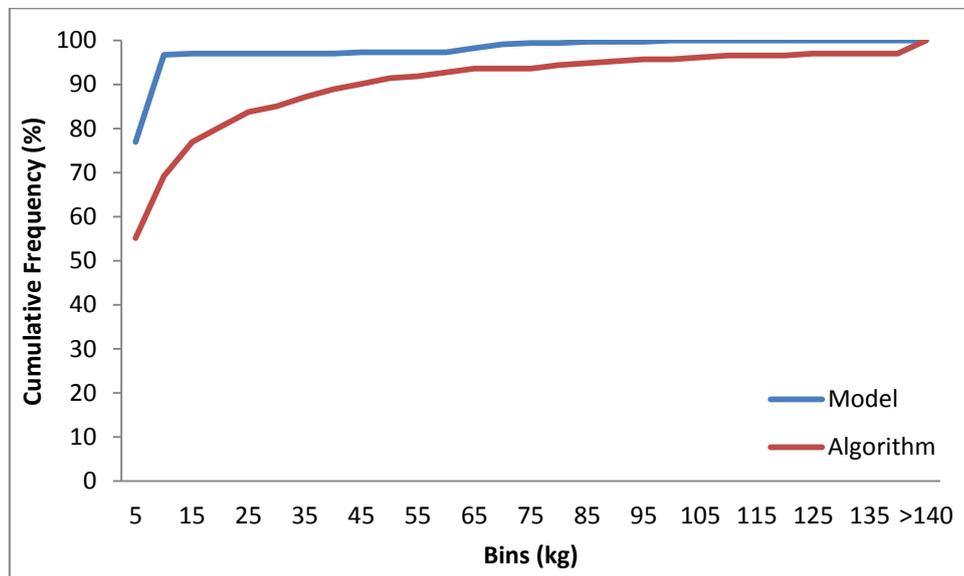


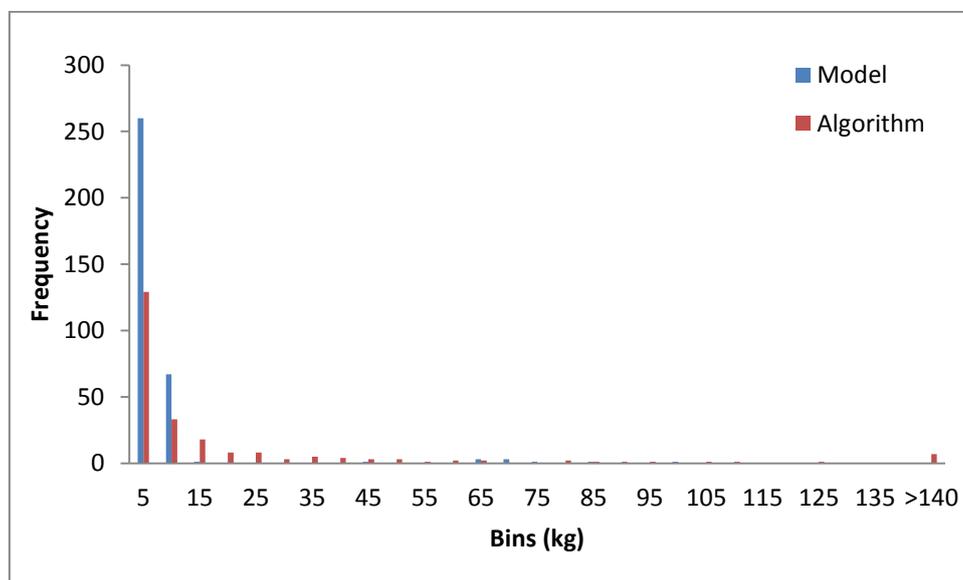
Figure 10b. Sensitivity of secondary forest growth model estimate of tree density to the parameters *Borreria* Seeding, *Borreria* Death and Patch Recovery.

Raising the probability of patch re-colonisation made the most impact on tree size distribution. Upon raising this probability to 0.9, 90% of all patches created were recolonized by grass and so patch formation was very limited, thus the spread of the *Borreria* was delayed. Because *Vismia* seeds rely on *Borreria* to germinate in our model parameterization, tree recruitment was in turn delayed. This resulted in many small trees after 12 years (fig 11a and b). Figures 11a and 11b show an over-estimation of very small trees by the model. This over-estimation resulted in the K-S test showing significant differences ( $\alpha 0.01$ ) between the algorithm and model estimates (fig 11a). The model estimated that 73% of the trees were  $\leq 5\text{kg}$  compared to the algorithm estimates of

56%. This resulted in the steep slope at the beginning cumulative frequency compared to the algorithm estimates (fig 11a). This is the main cause of the significant difference between the biomass estimates of the model and the algorithm. All other bin categories were under-estimated by the model.



**Figure 11a. Cumulative frequency(%) of tree biomass from automated tree crown delineation algorithm and secondary forest growth model estimates of a 12-14 year old neo-tropical secondary forest**



**Figure 11b. Distribution frequency (kg) of tree biomass from automated tree crown delineation algorithm and secondary forest growth model estimates of a 12-14 year old neo-tropical secondary forest.**

While varying the *Borreria* parameters affected tree density, the tree size distribution was not sensitive to them. This was due to tree density being only half as sensitive to these parameters as it was to patch re-colonization. Also, the probability of a cell being occupied by a *Borreria* plant

only affects the probability of it later being occupied by a *Vismia*, not the length of time *Vismia* has to grow. The reason behind this is most likely due to how tree biomass is calculated in the model. All trees in the shade have 10% growth rate of un-shaded trees. In our simulation, 92% of all trees were found to be in the shade after 12 years. This resulted in over-estimation of small trees.

## 4. Discussion

### 4.1 Algorithm Calibration

Crown delineation algorithms used on IKONOS images, in conjunction with our new crown diameter-to-biomass models, were successful at estimating the biomass distribution of the 12 to 14 year old secondary forest. The K-S test showing no significant difference between biomass calculated from algorithm crown diameter estimates and the field data. Although the algorithm and allometric equations accurately estimated biomass, the algorithm estimated mean tree crown width to be 3% smaller than field data estimates. This result corresponds exactly to previous results by Palace *et al* (2008). Their field data included crown width measurements as well as dbh measurements. When they discounted under-storey trees from the field data this error was reduced. The field data for this study does not distinguish between canopy and under-storey trees and our field data crown estimates are calculated from dbh measurements, still, these results are informative as they show the potential use the algorithm on forests with varying structures crown.

While the mean crown diameter was under-estimated, the minimum and maximum diameters were over-estimated. The over-estimation of maximum crown diameter is most likely due to the merging of tree crowns. Palace *et al* (2008) found this to be a re-occurring problem with the algorithm. This merging could be due to the presence of lianas growing along tree crowns, although this requires additional study.

Conversion of the of crown diameter to biomass using two allometric equations led to the large significant difference in biomass estimates. Feldpausch *et al* (2004) used separate allometric biomass equations for the most dominant species and then used a mixed species equation for all other trees. This study only used the mixed species equation to convert dbh to biomass as the algorithm could not distinguish species from the image. This may have contributed to the inaccuracy of the biomass estimates. For example, biomass estimated for a 5.32 cm diameter tree, our sample mean, would vary between 4.68kg and 9.67kg based on species specific or the mixed-species equation. These forests are predominantly dominated by *Vismia*, so biomass estimates could be more accurate if they were calculated using an allometric

equation developed specifically for *Vismia*.

There were no significant differences in biomass distribution found between images of the different sizes areas even though mean biomass and tree density differed between the three smallest images. These differences are most likely due to forest variations in forest structure across the landscape as the images are of slightly different areas. Also, Palace *et al* (2008) developed the algorithm to delineate tree crowns of primary tropical forests which had an average width of 12 m. When the field dbh data was converted to crown size using equation 2, the average crown diameter was 1.9m. This is very close to the image resolution of 1m. For accurate tree crown size estimates the spatial resolution should be considerably higher than the crowns in the image (Culvenor, 2003; Wulder *et al*, 2004). In a study of semi-automated individual tree crown analysis, Leckie *et al* (2003) found that young trees with small crowns led to clustering of tree crowns. The tightly packed canopy of the young secondary forest used in this study most likely led to the algorithms under-estimation of small trees and over-estimation of large trees.

The algorithm grossly under-estimated density of trees of all size classes. It has been found by many (Leckie *et al*, 2003; Gonzales *et al*, 2010; Palace *et al*, 2008) that delineation algorithms often under-estimate tree density. Indeed, Gonzales *et al* (2010) found that using the algorithm by Palace *et al* (2008) on primary and secondary forests in California; tree density was under-estimated by up to 50%. This is most likely due to the in-ability of the algorithm to count under-storey trees. Adjusting the field data to match the algorithms estimate of tree density (1728 trees/ha) by removing the smallest trees showed that the algorithm measured stem frequency with a cut-off diameter of 6.5cm. It is assumed that smaller trees were not counted. Feldpausch *et al* (2007) found that *Cecropia* are fast growing and can reach 20-25m tall, whereas *Vismia* trees are much shorter, reaching a height of 8-12m. While the field site was a *Vismia* dominated forest, *Cecropia* trees were present. Thus it could be assumed that many of the *Vismia* were over-shaded by the larger *Cecropia* trees. However, the canopy structure of *Cecropia* and *Vismia* differ greatly, with *Cecropia* crowns wide and diffuse and *Vismia* crowns generally narrower for a given diameter (Lucas *et al*, 2002).

Biomass estimates were almost insignificantly sensitive to the rise threshold when compared to the drop. The drop is a new concept for the algorithm and was used for the first time in this study. The rise limits the change in pixel to pixel brightness whereas the drop limits the change in brightness from the crown centre to crown edge. Therefore, the drop would always have a larger value than the rise and is thus has a larger effect on the estimated crown size. This allows for easier calibration of the algorithm than using the rise alone.

## **4.2 Model Parameterisation**

The tree biomass frequency distribution is only sensitive to the patch re-colonisation parameter as this is the only parameter (under low farming intensity) that prolongs the life of the pasture and thus delays the spread of weeds. The high value of this parameter represents the low impact that low intensity grazing has on patch formation.

While the model accurately estimates tree density and total biomass (Melling, 2009) it does not accurately estimate tree size distribution. The inability to parameterise the model to fit the field data was due to the continual over-estimation of very small trees and under-estimation of larger ones. This is most likely due to the biomass function as all trees that are shaded have a growth rate of 10% of un-shaded trees. The under-storey of secondary forests is comprised of many species of trees (Uhl *et al*, 1988). Documentation on the growth rates of under-storey species of young secondary tropical forests is rare but the average species biomass data from Feldpausch *et al* (2004) (table 1) indicates that it is varied. Feldpausch *et al* (2007) found that *Cecropia* and *Vismia* species have different growth rates and it can be assumed that the other tree species in the field data have differing growth rates also. This leads to a biomass distribution that is less skewed than the model estimates as some trees are growing faster than others. The model therefore needs to account for these differences by including a more stratified function for calculating growth rates of shaded and un-shaded trees. Presently, there are only two different growth rates in the model. A higher number of growth rates would decrease the skewness of the biomass distribution and allow the model to estimate the biomass distribution more accurately.

## **5. Conclusion**

The aim of this study was to calibrate a tropical secondary forest model using a panchromatic IKONOS image and an automated crown delineation algorithm. The algorithm accurately estimated tree biomass distribution of the 12-14 year old forest in the IKONOS image with accompanying field measurements, but under-estimated mean biomass and tree density. The under-estimation of mean biomass could be due to the use of only one allometric equation to convert all tree dbh estimates to biomass when multiple equations were used for the field data. The inaccurate tree density estimate has been found to be a common problem with tree crown delineation techniques since under-storey trees are not visible.

The models simplification of plant species present in secondary forest led to the over-estimation of very small trees. Future work should involve creating a stratified biomass function that represents trees with different growth rates.

The hypotheses of this study were:

- a) High-resolution IKONOS images used in conjunction with a tree-crown delineation algorithm can be used to delineate secondary forest tree crown diameters. Based on the relationship between crown diameter and field-measured tree diameter and aboveground biomass, IKONOS-based delineated tree crowns can be used to estimate tree size distribution (TSD) of secondary forests in the Manaus region, Amazonas.
- b) Remotely sensed high spatial resolution images of Amazonas secondary forest can be used to calibrate a growth model that simulates the effects of previous land-use intensity on tree size distribution of Amazonian secondary forests (Rebel *et al*, 2002). There will be no significant differences between TSD results from the model, those estimated using the remotely sensed images and those measured in the field.

From the results of the study hypothesis a) can be accepted. While hypothesis b) must be rejected, adjusting the models biomass function would solve the problem of the over-estimation of small trees. The findings of this study can have a positive impact on future work involving the monitoring of secondary forest growth which has historically been difficult due to lack of permanent sampling plots and insufficient satellite image resolution (Clarke *et al*, 2004). The estimation of tree biomass through tree crown delineation, allometric equations and modelling can make monitoring forest growth over large areas much more efficient and cost effective our results indicate this technique has potential for neo-tropical secondary forests.

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