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Supplementary Information

Mapping Above-Ground Biomass in a Tropical Forest in Cambodia Using Canopy Textures Derived from Google Earth. *Remote Sens.* 2015, *7*, 5057-5076

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This supplementary material supports the main text as follows:

Table S1 Field Measured Variables Used in the Study: The main field derived variable used in the study are AGB (derived by substituting Field measured diameter and tree height into Chave *et al.*, [25]) and ground measured percentage canopy cover (measures using field densitometer)

Ground canopy cover is described as the vertical projection of plant foliage onto a horizontal surface [S1]. GRS Densitometer was used for estimating % canopy cover at plot scale by using a transect methods. The vegetation cover at each point is recorded at a given location and the overall % canopy cover is calculated by dividing this with total number of points sampled [S2]. Canopy cover assessment is carried out by looking through the GRS Densitometer which is a periscope like device.

Table S1. Field Measured Variables Used in the Study.

Plot	Basal Area (sq m/ha)	Ground Based Canopy Cover%	AGB (Mg/ha)
1	45	54	221.92
2	50	52	220.90
3	47.7	63	246.39
4	53.7	60	294.27
5	51.7	58	264.75
6	69.4	69	314.04
7	55.8	61	223.43
8	68.6	64	302.86
9	55.9	61	244.46
10	59.2	64	286.95
11	56.7	60.5	285.51
12	32.5	48	119.61
13	26.3	41	94.05
14	26.8	44	97.61
15	21	35	60.79
16	19	45	69.23
17	32.9	55	213.95
18	34.1	56	149.52
19	22.5	52	149.08
20	29.4	45	138.20
21	17.9	61	50.98
22	44.1	66	211.63
23	51.7	74	302.95
24	48.7	51	356.16
25	22.7	48	136.16

Table S2 Vertical Canopy Structure: LiDAR derived CHM was used for deriving maximum canopy height (Max_CH) at 1ha plot scale.

FUSION/LDV is a freeware software which provides an intuitive and easy workflow for processing LiDAR point clouds [28]. It has been used for tropical forestry studies for processing LiDAR point clouds and deriving individual and plot scale metrics. FUSION/LDV implements the ground filtering algorithm (using an in-built functionality known as "GroundFilter"). This algorithm identifies the returns that lie close to the ground and classifies them as the bare earth points. These bare earth points are used to create a gridded surface model or the DTM (using an in-built functionality known as "Grid Surface Create"). The DTM thus created is considered to be adequate for facilitating the calculation of vegetation heights. Please see the following workflow for different processing steps undertaken for generating a CHM from LiDAR point clouds in FUSION/LDV.

Table S2. Vertical Canopy Structure.

Plot	Maximum Canopy Height (Max_CH) at 1 ha Scale
1	19.4
2	21.1
3	24
4	26.7
5	22.5
6	26.4
7	16.4
8	19.1
9	27.3
10	26.2
11	23.2
12	21.2
13	13.7
14	16.6
15	9.8
16	11
17	23.2
18	22.6
19	17.2
20	16.9
21	11.3
22	26.3
23	21.2
24	20
25	21.1
Mean ±SD	20.1 (± 5.1)

Creation of the said ground surface model or DTM involves using the average of elevations from each off the grid cells to produce the gridded/rasterized DTM model. Hence an interpolation step is indeed needed to project the 3D LiDAR point cloud onto a 2D rasterized surface (in this case DTM which in turn is used as an input to generate a CHM). Smoothing is carried out to remove any remainder vegetation (such as shrubs *etc.*) which maybe left on the surface model. However smoothing of the DTM is carried out well after the classification of LiDAR points into bare-earth points and non-ground points and is entirely optional. Hence creation of the gridded raster and its smoothing do not influence the classification of LiDAR points (which as is shown in the flowchart is the primary starting point). Further FUSION/LDV has been designed with forestry applications in mind and can carry out accurate point classifications for LiDAR point clouds with density > 4 points/m^2. FUSION is very effective in creating accurate CHMS even for dense tropical forests. The upshot of the approach is that the LiDAR points are classified into ground and non-ground points before modelling.

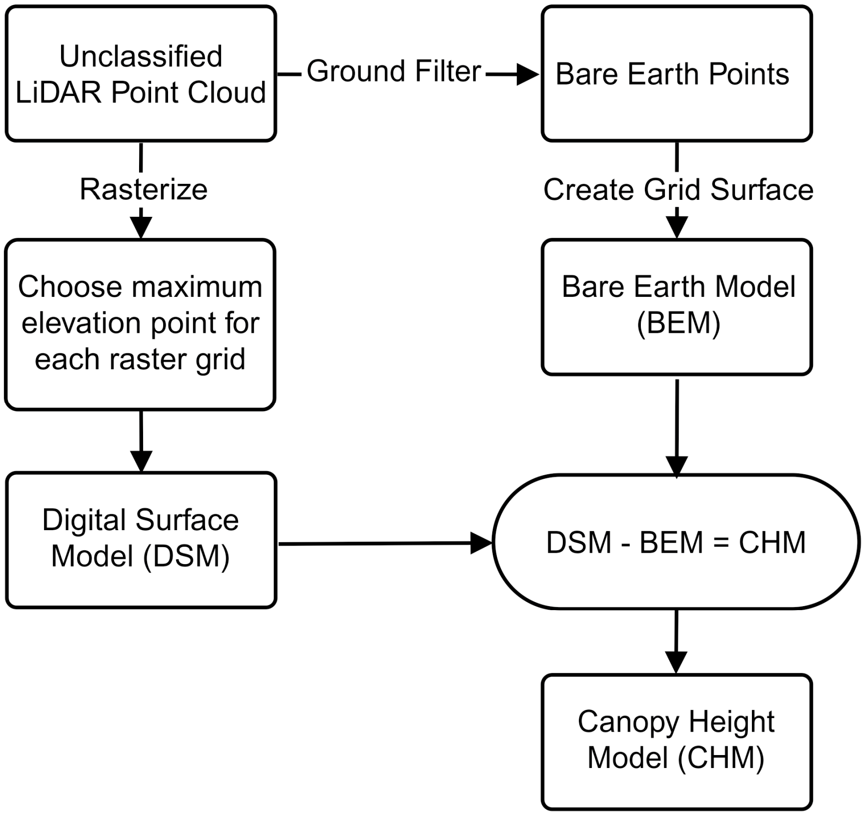

Figure S1. Deriving CHM data from LiDAR Point Clouds.

Tree heights of all the trees in the 25 plots could not be measured. Instead tree heights and DBH were measured for 150 trees. Size-stratified random sampling was carried out with the view of ensuring that both large trees as well as relatively smaller trees were included. See table.

Table S3. DBH-Height Relationships.

DBH (in cm)	Tree Height (in m)
138.95	35
33.7	22.5
114.17	30.5
173.9	32.8
46.66	24.5
21.35	18.2
47.58	23.5
962.53	45.8
35.65	20.9
24.07	17.6
25.46	22.3
36.15	21.6
28.08	19.3
35.65	21.5
15.8	25
33.7	34.4
32.31	28.5
12.8	35.9

Table S3. *Cont.*

DBH (in cm)	Tree Height (in m)
46.53	23.4
119.08	38.9
122.47	30.3
153.28	31.9
27.62	19.7
181.43	33.45
163.16	37.8
23.08	18.4
33.7	21.1
1420.5	49.1
251.55	35.43
56.51	24.79
32.25	22.3
164.41	32.4
24.67	19.8
132.66	30.87
58.13	24.99
108.42	29.5
38.96	24.6
121.34	30.23
27.51	22.3
173.12	37.9
44.5	39.43
39.95	33.4
144.51	38.8
35.7	37.55
43.38	22.9
118.9	46.5
9.07	11.74
52.79	24.3
120.76	30.2
28.48	19.9
47.8	57.8
108.9	33.35
14.73	15.2
125.03	30.45
54.69	24.55
173.94	32.8
125.03	30.45
54.69	24.55
107.3	45
31.76	20.68
46.11	23.34
124.53	30.42
124.33	30.41
67.31	26.03

Table S3. *Cont.*

DBH (in cm)	Tree Height (in m)
294.37	36.55
4.25	6.33
3.46	4.88
5.86	8.63
57.09	24.86
88.85	28.01
98	30.42
142	47.88
29	26.03
16	20.25
78	29.39
162	35.30
123	33.07
8	14.15
11.5	16.89
78.1	30.32
13	18.05
16.1	19.30
14.1	19.40
30	22.90
44	26.82
20	20.85
14	17.40
27.8	23.97
80.1	30.15
20	19.90
8	13.92
10	15.27
27	22.41
22.1	20.96
7	14.55
37.1	24.69
13	18.47
11	16.77
16.5	20.07
26.1	23.29
127	33.79
11.5	16.23
23.1	22.12
28	23.57
11	17.59
14	19.31
11	17.34
9	16.29
19	19.70
10	16.11

Table S3. *Cont.*

DBH (in cm)	Tree Height (in m)
10	16.04
17.1	19.38
11	16.43
11	15.74
12	18.14
13.1	18.16
11	16.57
18	19.16
16.1	19.74
22	20.89
10	16.24
13.1	18.18
23	21.51
10.5	16.46
9	14.45
13.1	18.51
10	15.04
12	17.70
12	18.11
140	33.35
8	14.02
8.5	14.26
15	17.84
64	28.70
10	15.45
11	17.34
11	16.57
12.1	18.00
14	19.34
42	25.98
28	23.88
24	21.96
24	21.96
18.1	21.00
21	20.89
10	15.41
9	14.61
14	18.37
12.1	17.33
19	20.50
14	18.41
12.1	17.33
19	20.50
14	18.41

As Morel *et al.* [S3] recommends, regression relationship was derived between field measured tree height and natural log DBH in cm.

$$Height = 6.9 \times Ln(DBH) + 0.17 \quad (1)$$

(here $R^2 = 0.74$ and $p < 0.001$).

For trees whose actual heights had not been measured in the field, their heights were estimated using the DBH-Height relationship derived using the above equation.

2D FFT is applied on the imagery to ultimately obtain the r-spectra. PCA is ultimately intimated on this to obtain the texture indices as adopted from Singh *et al.* [14].

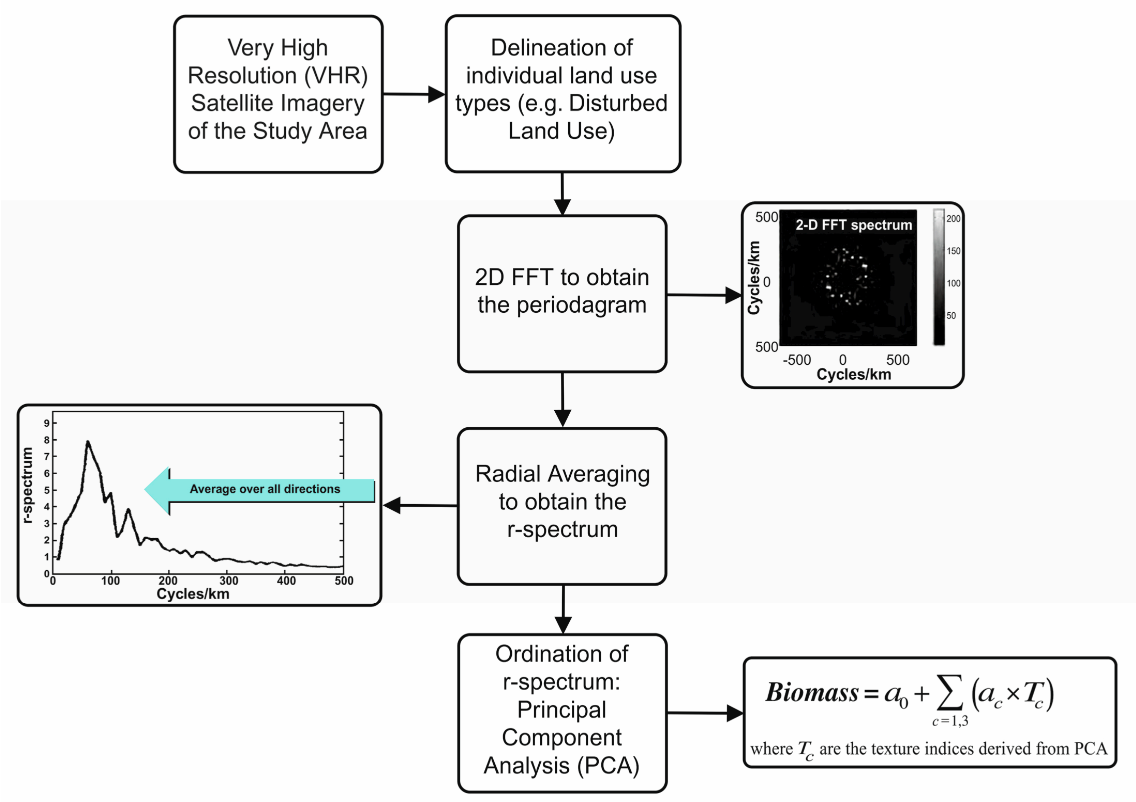

Figure S2. Workflow of the FOTO Algorithm.

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