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Research Paper

Influence of micro-topography and crown characteristics on tree height estimations in tropical forests based on LiDAR canopy height models

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ABSTRACT

Tree or canopy height is an important attribute for carbon stock estimation, forest management and habitat quality assessment. Airborne Laser Scanning (ALS) based on Light Detection and Ranging (LiDAR) has advantages over other remote sensing techniques for describing the structure of forests. However, sloped terrain can be challenging for accurate estimation of tree locations and heights based on a Canopy Height Model (CHM) generated from ALS data; a CHM is a height-normalised Digital Surface Model (DSM) obtained by subtracting a Digital Terrain Model (DTM) from a DSM. On sloped terrain, points at the same elevation on a tree crown appear to increase in height in the downhill direction, based on the ground elevations at these points. A point will be incorrectly identified as the treetop by individual tree crown (ITC) recognition algorithms if its height is greater than that of the actual treetop in the CHM, which will be recorded as the tree height. In this study, the influence of terrain slope and crown characteristics on the detection of treetops and estimation of tree heights is assessed using ALS data in a tropical forest with complex terrain (i.e. micro-topography) and tree crown characteristics.

Locations and heights of 11,442 trees based on a DSM are compared with those based on a CHM. The horizontal (D_H) and vertical displacements (D_V) increase with terrain slope ($r = 0.47$ and $r = 0.54$ respectively, $p < 0.001$). The overestimations in tree height are up to 16.6 m on slopes greater than 50° in our study area in Sumatra. The errors in locations (D_H) and tree heights (D_V) are modelled for trees with conical and spherical tree crowns. For a spherical tree crown, D_H can be modelled as R sin θ, and D_V as R (sec θ – 1). In this study, a model is developed for an idealised conical tree crown, $D_V = R(\tan\theta - \tan\psi)$, where R is the crown radius, and θ and ψ are terrain and crown angles respectively. It is shown that errors occur only when terrain angle exceeds the crown angle, with the horizontal displacement equal to the crown radius. Errors in location are seen to be greater for spherical than conical trees on slopes where crown angles of conical trees are less than the terrain angle. The results are especially relevant for biomass and carbon stock estimations in tropical forests where there are trees with large crown radii on slopes.

1. Introduction

Tropical rainforests play an important role in regulating the Earth's climate by being a large sink for carbon dioxide (Corlett, 2016; Thomas and Baltzer, 2001). An accurate estimation of carbon components within a forest is a first step in the recent United Nations initiative for Reducing carbon Emissions from Deforestation and forest Degradation (REDD). However, limited knowledge about the quantity and spatial distribution of biomass at the landscape level has led to considerable uncertainties in the estimation of carbon stocks (Mascaro et al., 2011). Canopy height is an important component of biomass/carbon stock estimates in forests (Hudak et al., 2012).

Tropical forests also support a large proportion of the Earth's plant and animal species, many of which are endangered by increasing deforestation and forest degradation leading to fragmentation of habitats (Thomas and Baltzer, 2001). Field-based surveys of habitats are difficult for tropical forests in terms of access, and the species diversity is extremely high while the existing knowledge of taxonomy is relatively poor (Salovaara et al., 2005). Remote sensing can be an efficient source of information for mapping these forests, and to identify habitats for more detailed field surveys (Moran et al., 1994; Salovaara et al., 2005).

Large trees account for most of the biomass in tropical forests, serve as a focal point for biological activity and create large gaps at death, altering the forest structure dynamics in addition to releasing the sequestered carbon (Chambers et al., 2007; Ferraz et al., 2016). Presence of tall trees would be a useful input for modelling species distributions

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and assessing the quality of habitat for many species including birds and arboreal primates (Lesak et al., 2011). For example, emergent trees are the preferred resting and sleeping places for endangered primates such as siamangs, gibbons and langurs (Nijman and Geissman, 2008). Canopy or tree heights are therefore also important for understanding the habitat preferences of species and for devising conservation strategies for species threatened by the destruction and degradation of their habitats.

Light Detection and Ranging (LiDAR) has significantly contributed to the remote sensing of forests in the last two decades (Dubayah and Drake, 2000; Lim et al., 2003). This is mainly due to the capability of LiDAR to collect data in the form of x, y and z locations of points (often referred to as a point cloud), even from the ground below forest canopy. Airborne Laser Scanning (ALS), using a LiDAR sensor from an airborne platform, has been extensively used for deriving structural attributes of forest canopies. ALS provides information about the three-dimensional structure of forests, which provides an additional perspective of the habitat needs and requirements of species compared to two-dimensional satellite imagery (Bergen et al., 2009; Coops et al., 2016). Canopy height is an important attribute which can be used to derive other forest structural characteristics such as stand volume, basal area and above-ground biomass (AGB).

The ALS point cloud is initially classified into ground and non-ground; this process, known as ground filtering, is still an active area of research, especially in complex terrain and forests (Maguya et al., 2014; Yang et al., 2016). A Digital Terrain Model (DTM) is generated from the ground points (Axelsson, 2000; Kraus and Pfeifer, 1998; Sithole and Vosselman, 2004), and the highest points, or the 95th percentile to avoid outliers (Kane et al., 2010), within grid cells are typically used to generate a Digital Surface Model (DSM). A Canopy Height Model (CHM), which represents the height of canopy above the ground, can then be derived by subtracting the DTM from the DSM.

Delineation of individual trees from ALS data is a topic which has received considerable attention from researchers in forestry. The first step in most algorithms for delineating tree crowns based on a CHM is the detection of treetops based on local maxima within predefined windows (kernels). The grid cells belonging to a tree crown are then delineated or "grown" from adjacent cells with lower height or elevation values, often using a watershed algorithm. The algorithm terminates when there are no more cells adjacent to, and lower than, the detected cells (Chen et al., 2006; Popescu and Wynne, 2004).

Dense forests on complex terrain, especially on steep slopes, are considered to be challenging both for the generation of accurate DTMs and for the height estimation of forest stands and individual trees. Fewer points from the ground may be collected from below dense forests, reducing the accuracy of the generated DTM since local variations in micro-topography, such as peaks and pits, may not be detected. The ground below points of a tree crown on sloping terrain, in the downslope direction, are lower than the ground below the tree top, causing an upward shift in the height percentiles of forest stands with increasing slope (Breidenbach et al., 2008; Khosravipour et al., 2015).

ALS is increasingly being used to characterise tropical forests and quantify above-ground biomass, where approaches are based either on the characteristics of individual tree crowns or grid-based models (Asner and Mascaro, 2014; Asner et al., 2012; Ferraz et al., 2016; Vaglio Laurin et al., 2016). The influence of slope and crown characteristics on the estimation of tree locations and heights in tropical forests on complex terrain has not yet been analysed or modelled. Since carbon stock estimations are based on canopy and individual tree heights to a large extent (Ioki et al., 2014), it is important to assess the influence of slope on height estimations from ALS data.

It has been noted that height-normalisation of a DSM or the point cloud, based on a DTM, could introduce errors in the case of sloping terrain (Vega et al., 2014), and the estimation of tree locations before normalisation may be a better alternative. However, there has been only one attempt to quantify the influence of terrain slope on the estimation of tree locations and heights. Tree heights were shown to be overestimated by up to 1.8 m for Scots pine (*Pinus sylvestris*) trees for terrain slopes above 30°, while there was no influence of slope on height estimates of conical mountain pine (*Pinus uncinata*) trees, in an analysis of 395 trees belonging to the two species (Khosravipour et al., 2015). However, the crown radii of Scots pines did not have a correlation with errors in height estimation, as would have been expected from a theoretical model.

The aim of this study is to assess the influence of slope and crown characteristics on the detection of treetops and estimation of tree heights using ALS data in a tropical forest with complex terrain and tree crown characteristics. The first objective is to estimate the differences in the locations and heights of trees using a DSM and a CHM generated from ALS data; the CHM-based method is more widely used and implemented in software packages (Chen, 2007; Chen et al., 2006; Kini and Popescu, 2004; McGaughey, 2015). The second objective is to assess the effect of slope on the horizontal and vertical displacements in the detected treetops using the two methods. The third objective is to model the differences in estimated tree height based on terrain slope and tree crown characteristics, using crown slope in addition to crown radius, thereby extending the model developed by Khosravipour et al. (2015). This could provide a method to model errors in above-ground biomass and carbon stock estimations based on terrain and tree crown characteristics.

2. Materials and methods

2.1. Study area and dataset

The study area is in Batang Toru (1° 49′N, 99° 5′E), in the Indonesian province of North Sumatra, and covers an area of approximately 14.7 km^2. The Batang Toru forests are home to a number of unique plant and animal species including the critically endangered Sumatran orang-utans (*Pongo abelii*), Malayan tapirs (*Tapirus indicus*) and Sumatran tigers (*Panthera tigris sumatrae*).

ALS data were collected between 23rd March and 4th April 2015, using a Leica ALS-70 HP LiDAR system from a fixed wing aircraft for an area of 162 km^2. The flying height was between 900 m and 1350 m above ground level, and the scan half angle was 22.5°. This generated an ALS point cloud with an average density of 12 returns m^{-2} (Alexander et al., 2017). The returns were classified into ground and non-ground using an algorithm based on adaptive Triangulated Irregular Network (TIN) filtering implemented in Terrasolid software, and divided into 240 (1 km × 1 km) tiles for both the ground returns and non-ground returns (Axelsson, 2000; McElhanney, 2015). Sixteen tiles from this dataset were used for this study.

2.2. Generation of terrain, surface and canopy height models

A DTM with a grid cell size of 1 m was generated using the mean elevation of all ground returns within each cell in FUSION v3.60 (McGaughey, 2015). The cells that did not contain any returns were filled by interpolation. The slope of each grid cell in the DTM was calculated in ArcGIS™ 10.1 based on the maximum rate of change in value from that cell to its eight neighbours.

The ground and non-ground returns were merged in FUSION. A DSM at a grid cell size of 1 m was generated from these points using the *CanopyModel* function, which assigns the highest elevation within each grid cell to that cell. A CHM which represents the height of each cell above the ground was generated by subtracting the DTM from the DSM.

2.3. Detection of treetops

Most algorithms for identifying treetops using ALS data locate the local maxima within windows of variable sizes (Popescu and Wynne, 2004; Popescu et al., 2002). The window sizes are determined by

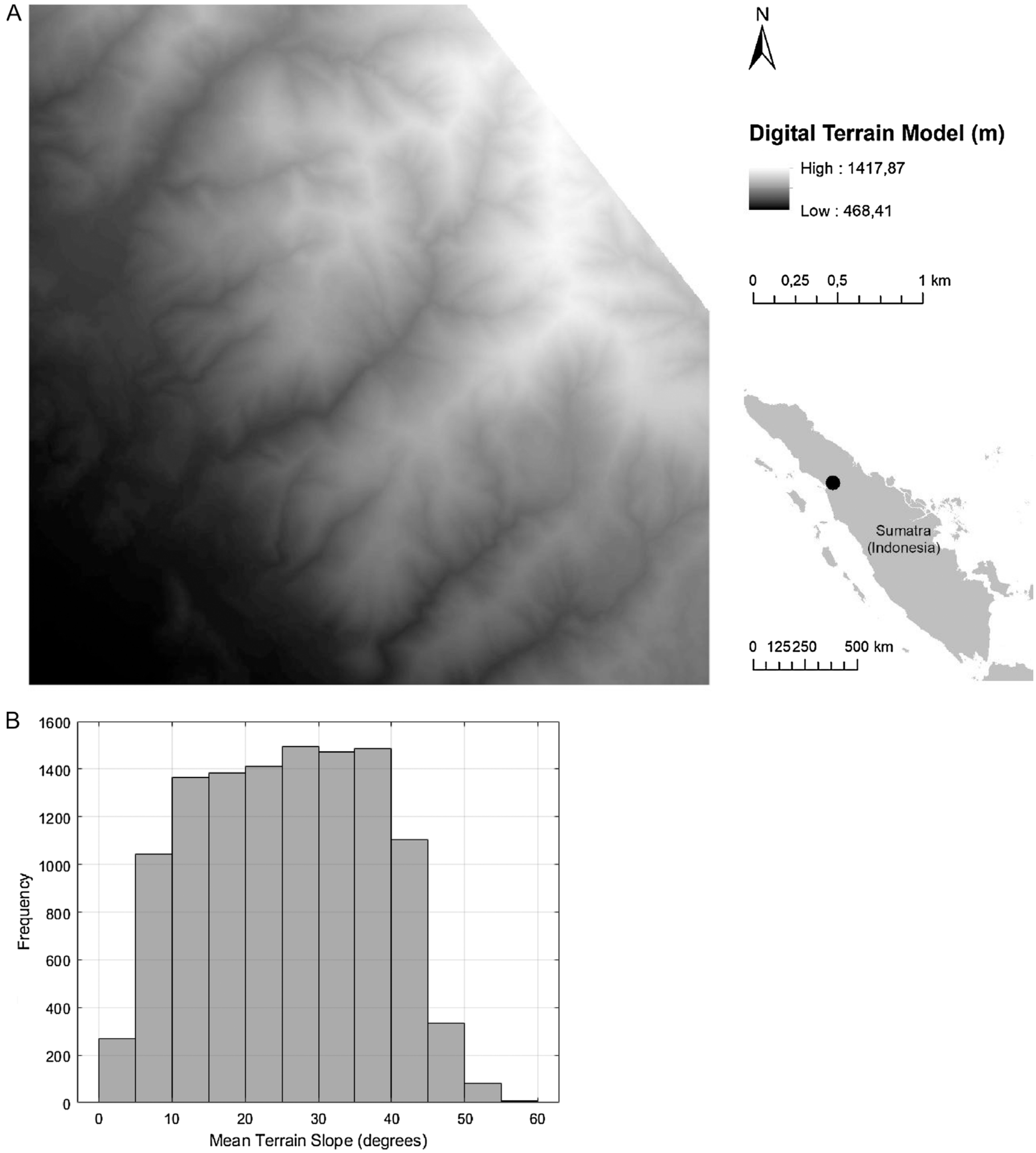

Fig. 1. Digital Terrain Model of the study area (A); Distribution of mean terrain slope (B).

equations using the height of the cell under consideration, and coefficients generated from tree height and crown width measurements in similar forests. For example, the default equation for calculating the window size for detecting local maxima in FUSION is $2.51503 + 0.009{*}ht^2$ where *ht* is the canopy surface height from a CHM (Kini and Popescu, 2004; McGaughey, 2015). A fixed circular window of 15 m radius was used in this study to detect treetops (local maxima) in both the DSM and the CHM since the height-specific window sizes could not be determined for the DSM. A height threshold of 10 m was used for detecting treetops in the CHM, to limit the number of detected trees to tall, large, trees which would be more useful for addressing the objectives than smaller trees. The elevations of cells identified as treetops in the DSM were subtracted from the corresponding grid cell values in the DTM to calculate the heights of trees, and trees taller than 10 m were selected for further analysis.

Treetops generated from the CHM ($Trees_{CHM}$) that were closest to the treetops generated from the DSM ($Trees_{DSM}$), and within 10 m radii, were considered to belong to the same trees; a buffer of 10 m was considered to be sufficient to detect maxima in the CHM and the DSM within the same tree crown. A second criterion was used to reduce the possibility of comparing adjacent treetops; treetops in $Trees_{DSM}$ and $Trees_{CHM}$ were considered to belong to the same tree only if the treetop in $Trees_{CHM}$ was within the tree crown in $Trees_{DSM}$ delineated using a watershed algorithm (Gougeon, 1995). The DSM was first inverted (multiplied by -1) so that all the treetops were located at the local minima points. A raster of flow direction from each cell to its steepest downslope neighbour was created. The downslope area contributing to the location of each treetop, or the upslope area contributing to each outlet, was delineated using the Hydrology toolbox in ArcGIS™. Only $Trees_{CHM}$ within the tree crown area of adjacent $Trees_{DSM}$ were selected for further analysis.

In the cases where more than one tree in $Trees_{CHM}$ occurred inside a single tree polygon in $Trees_{DSM}$, the duplicates were removed by selecting the tree in $Trees_{CHM}$ which was the closest to the corresponding treetop in $Trees_{DSM}$. Points which are above a certain height from the ground can be considered as outliers and ignored while generating a CHM, for example points above 150 m in forests. However, this method would not work for removing outliers from a DSM. The outliers were therefore removed later by removing treetops that were above a height threshold from their neighbouring cells. The focal means of cells within a 3 × 3 window were calculated. If a detected treetop was three standard deviations higher than the mean, the treetop was considered as an outlier, and not considered for further analyses.

2.4. Comparison of the locations and heights of trees

The mean terrain slope was calculated from the DTM within a 10 m radius of the location of each treetop for the selected $Trees_{DSM}$. The locations and heights of trees from $Trees_{CHM}$ closest to the selected $Trees_{DSM}$ were then identified, and the attributes transferred across. Each treetop in $Trees_{DSM}$ now held information on its X and Y co-ordinates, height and mean terrain slope within a 10 m radius, plus the first three attributes for the corresponding treetop in $Trees_{CHM}$ and the horizontal distance between the treetops (D_H), as its attributes. The differences in heights between corresponding treetops in $Trees_{DSM}$ and $Trees_{CHM}$ were also calculated (D_V). Statistical analysis (Student's *t*-test, $p < 0.001$) was performed in MATLAB to test whether the heights of $Trees_{CHM}$ were significantly different from $Trees_{DSM}$.

2.5. Modelling the differences in estimated tree heights

The displacements of treetops in $Trees_{CHM}$ from the treetops in $Trees_{DSM}$, in the horizontal and vertical directions, were analysed to determine the relationship of displacements with terrain slope and tree crown characteristics. These were used to develop a model to quantify the potential errors in the estimation of tree locations and heights from a CHM on sloped terrain. Trees with conical crowns were found to be useful in modelling the relationship between terrain slope, crown characteristics and displacements in the locations and heights of trees. Trees with spherical crowns were used mainly to compare the model developed in this study to that developed by Khosravipour et al. (2015). Statistical analyses (Pearson's correlation, α: 0.001) were performed to test whether the horizontal and vertical displacements of treetops were correlated with each other and with terrain slope.

3. Results and discussion

3.1. Locations and heights of trees

The classified ground returns in the study area had an average density of 0.32 returns m^{-2}. The terrain elevation ranged from 468.3 to 1417.9 m (Fig. 1A). The maximum terrain slope was 80.7°, and the mean slope within a 10 m radius of cells ranged from 0.4 to 58.7° (Fig. 1B).

There were 21,977 detected trees in $Trees_{DSM}$ that were taller than 10 m, and there were 11,671 trees in $Trees_{CHM}$ that were within 10 m of the treetops of $Trees_{DSM}$ and within their crown polygons (Fig. 2). This was reduced to 11,442 treetops when outliers and duplicates were removed. The mean height of trees in $Trees_{DSM}$ (after terrain normalisation) was 31.39 ± 9.85 m, while the mean height of trees in $Trees_{CHM}$ was 31.86 ± 10.22 m. The mean horizontal displacement was 1.46 ± 1.84 m, with no horizontal displacement for 5038 (44%) of the trees. The mean vertical displacement between $Trees_{DSM}$ and $Trees_{CHM}$ was 0.47 ± 0.87 m, with 3011 (26.3%) trees in $Trees_{DSM}$ being taller or equal in height to $Trees_{CHM}$.

3.2. Influence of slope on estimated heights of trees and above-ground biomass

The horizontal distances between the treetops of $Trees_{DSM}$ and $Trees_{CHM}$ had a positive correlation with terrain slope ($r = 0.47$; $p < 0.001$). The median horizontal displacement was zero up to a mean terrain slope of 20°. The heights of $Trees_{DSM}$ were significantly greater than those of $Trees_{CHM}$ ($p < 0.001$), with the vertical displacement increasing with terrain slope ($r = 0.54$; $p < 0.001$) (Fig. 3).

3.3. Modelling vertical displacement of treetops

The angle that a line connecting a detected treetop and a point on the tree crown surface (DSM) makes with the horizontal plane, is hereafter referred to as the crown angle (ψ). The crown angle would be the same for every point on the surface of an idealised conical tree crown (Fig. 5). For a hemi-spherical tree crown, ψ would increase with increasing distance from the treetop, from 0° at the top to 45° when the distance from the treetop is equal to the crown radius. The angle that a line connecting the ground (DTM) points below a detected treetop and a crown point makes with the horizontal plane, is referred to as the terrain angle (θ; Figs. 4 and 5)

The vertical displacement of treetops (D_V) in $Trees_{CHM}$ in the study area was highly correlated with their horizontal (D_H) displacement ($r = 0.74$; $p < 0.001$). The vertical displacement was also correlated ($r = 0.60$; $p < 0.001$) with the slope between the terrain points (θ). The vertical displacement (D_V) was equal to the difference between the vertical displacements of the terrain (ΔT) and the canopy (ΔC; Eq. (1) and Fig. 4). For $0 \le \Delta C \le \Delta T$, D_V could be written in terms of the terrain and crown slopes (Eq. (2)), which could be simplified (Eq. (3)) as D_H (tan θ-tan ψ).

$$D_V = \Delta T - \Delta C \tag{1}$$

$$D_V = D_H \tan\theta - D_H \tan\psi \tag{2}$$

$$D_V = D_H(\tan\theta - \tan\psi) \tag{3}$$

Tree heights were overestimated in $Trees_{CHM}$ when there was any point on the crown envelope described by the DSM where ψ was less than θ (Fig. 4). There would be no horizontal or vertical displacement when ψ was greater than θ, since the treetop in $Trees_{DSM}$ would be higher than all the other points even after normalisation using a DTM. The horizontal displacement of the treetop in $Trees_{CHM}$ was equal to the horizontal distance between this point and the treetop. The vertical displacement was related to the difference between θ and ψ as well as the horizontal displacement.

The slope of individual cells of the DTM within the crown area from the ground elevation at the location of the trunk, or the treetop, has an influence on the overestimation of tree heights in $Trees_{CHM}$. These values were different from the mean terrain slope within a 10 m radius of the detected treetops in $Trees_{DSM}$. The slope between terrain points (θ) was correlated with the mean terrain slope ($r = 0.73$; $p < 0.001$). However there was a mean difference of 1.53 ± 9.12 m between the two values. The estimated heights of $Trees_{DSM}$ and $Trees_{CHM}$ would be the same for trees with a crown angle of 75° up to a terrain slope of 75°, for conical tree crowns (Fig. 5).

On the other hand, tree heights could be overestimated by almost 7 m for a tree with a radius of 2 m, crown angle of 15° and terrain angle of 75° (Fig. 6A). The overestimation could be above 40 m for a tree with a radius of 12 m, crown angle of 15° and terrain angle of 75° (Fig. 6B).

For a tree with a spherical or hemi-spherical crown, the maximum crown angle is 45° (Fig. 7) and occurs on the surface of the sphere on a horizontal plane through the centre. The crown angle decreases from this point to the top of the crown. The spherical crown is therefore more difficult to describe in terms of crown angle than a conical crown. The sagitta of a circular arc (h) is the distance from the centre of the arc to the centre of its base. This would represent the vertical distance from the treetop and can be calculated as

$$h = R - \sqrt{R^2 - D_H{}^2} \tag{4}$$

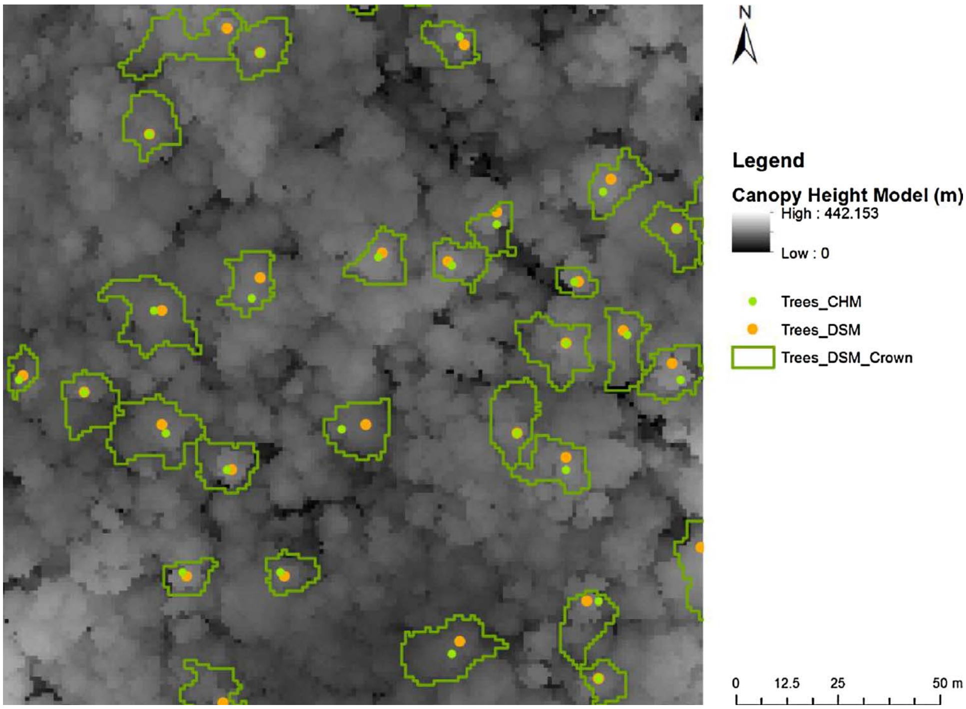

Fig. 2. Treetops detected in the Canopy Height Model ($Trees_{CHM}$) and Digital Surface Model ($Trees_{DSM}$), within the crown polygons of $Trees_{DSM}$; Local maxima were detected within circular windows of radius 15 m, and trees taller than 10 m were selected for analyses.

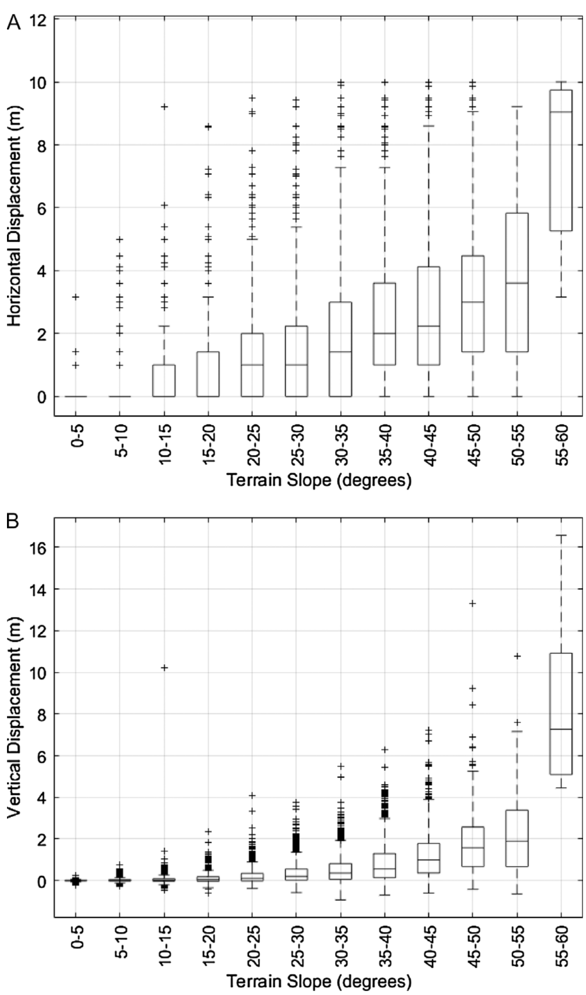

Fig. 3. Horizontal (A) and vertical (B) displacements between treetops detected in the Canopy Height Model ($Trees_{CHM}$) and Digital Surface Model ($Trees_{DSM}$), within the crown polygons of $Trees_{DSM}$, in relation to terrain slope.

where R is the radius and D_H is the horizontal displacement. Therefore, for any point on the spherical crown at a horizontal distance D_H from the treetop,

$$\tan\psi = h/D_H = (R - \sqrt{R^2 - {D_H}^2})/D_H \tag{5}$$

where ψ is the crown angle and R is the crown radius. The horizontal displacement at x is the distance at which the tree height based on the CHM, H_{CHM} is maximised.

$$H_{CHM}(x) = H_{DSM} + x\ tan\theta - x\ tan\psi = H_{DSM} + x\ tan\theta - x\frac{R - \sqrt{R^2 - x^2}}{x} \tag{6}$$

Replacing tanθ with m,

$$H_{CHM}(x) = H_{DSM} + mx - R + \sqrt{R^2 - x^2} \tag{7}$$

The horizontal displacement can be determined by solving for $H_{CHM}{}'(x) = 0$ (Khosravipour et al., 2015):

$$H'_{CHM}(x) = m + x/\sqrt{R^2 - x^2} = 0 \tag{8}$$

$$D_H = mR/\sqrt{1 + m^2} = R\ \tan\theta/\sqrt{1 + \tan^2\theta} = R\ \tan\theta/\sqrt{\sec^2\theta} = R\ \tan\theta/\sec\theta \tag{9}$$

$$D_H = R\ \sin\theta\ \cos\theta/\cos\theta = R\ \sin\theta \tag{10}$$

where D_H is the horizontal displacement, R is the crown radius and θ is the terrain angle.

Eq. (3) can be modified based on Eq. (5) and Eq. (10) as:

$$D_V = D_H(\tan\theta - (R - \sqrt{R^2 - {D_H}^2})/D_H) = R\ \sin\theta(\tan\theta - (R - \sqrt{R^2 - (R\ \sin\theta)^2}\ /D_H)) \tag{11}$$

$$D_V = R\ \sin\theta(\tan\theta - (R - \sqrt{R^2 - R^2 sin^2\theta})/R\ \sin\theta) = R\ \sin\theta(\tan\theta - (R - \sqrt{R^2(1 - sin^2\theta)}/R\ \sin\theta)) \tag{12}$$

$$D_V = R\ \sin\theta(\tan\theta - (R - \sqrt{R^2 cos^2\theta})/R\ \sin\theta) = R\ \sin\theta(\tan\theta - (R - R\ \cos\theta)/R\ \sin\theta) \tag{13}$$

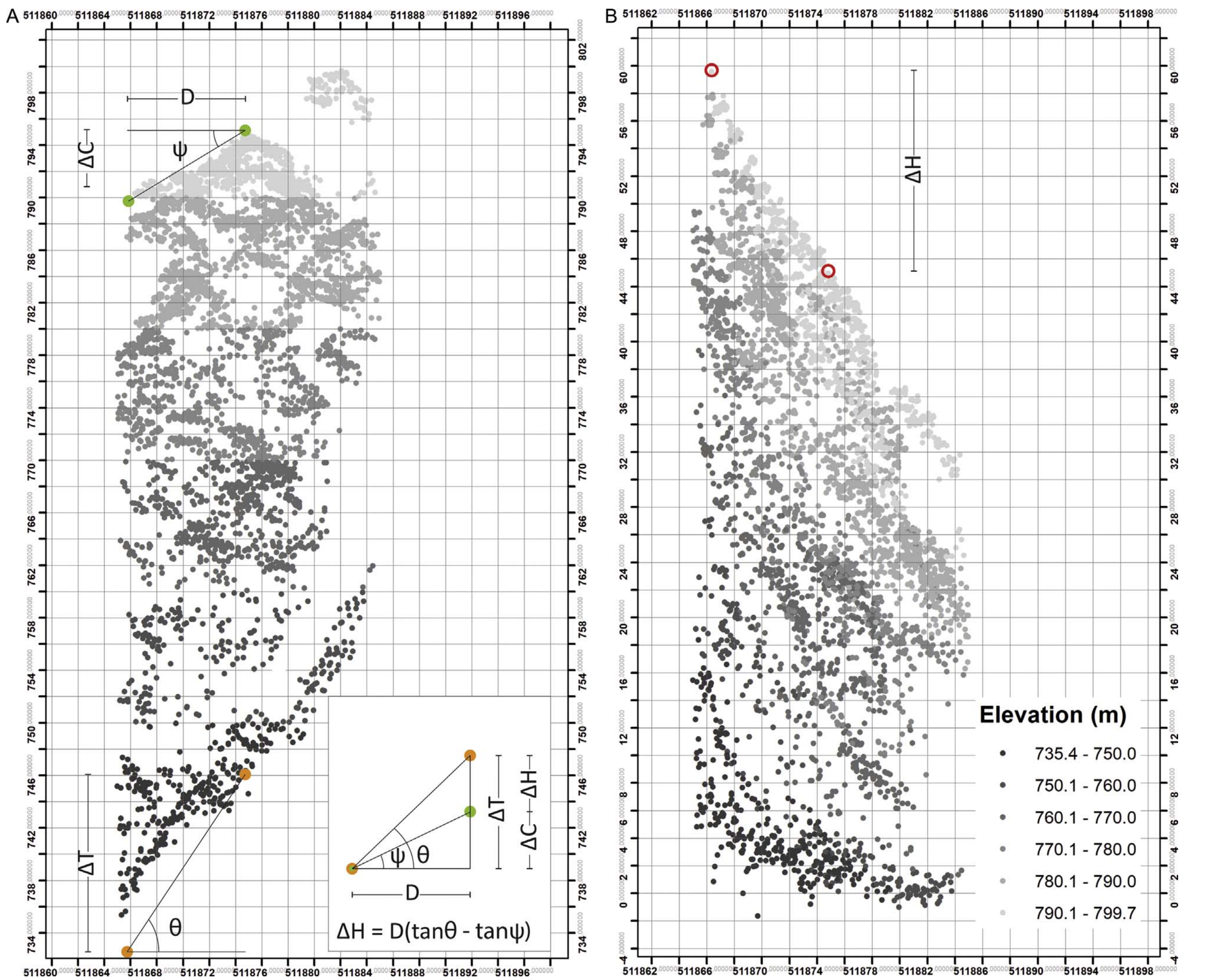

Fig. 4. Airborne Laser Scanner (ALS) points within 10 m radius of a detected treetop in the Digital Surface Model (DSM) coloured by elevation, with the estimated terrain and crown slopes (A); ALS points after normalising using a Digital Terrain Model (DTM) showing the detected treetops in the DSM (lower) and the Canopy Height Model (B); D_V = Vertical distance between estimated treetops (difference in heights); ΔT = Difference in terrain elevations; ΔC = Difference in actual treetop elevations; θ = Terrain slope; ψ = Crown slope; D = Horizontal distance between estimated treetops.

$$D_V = R\ \sin\theta(\tan\theta - R(1-\cos\theta)/R\ \sin\theta) = R\ \sin\theta\ \tan\theta - R + R\ \cos\theta \tag{14}$$

$$D_V = R(\sin\theta\ \tan\theta + \cos\theta - 1) = R(sin^2\theta/\cos\theta + \cos\theta - 1) \tag{15}$$

$$D_V = R((sin^2\theta + cos^2\theta - \cos\theta)/\cos\theta) = R((1-\cos\theta)/\cos\theta) \tag{16}$$

$$D_V = R(\sec\theta - 1) \tag{17}$$

The horizontal and vertical displacements of treetops for a tree with a spherical crown are therefore dependent only on the crown radius and the terrain slope (Fig. 7).

The horizontal and vertical displacements for a tree with a spherical crown increase steadily with terrain slope, with the maximum horizontal displacement equal to its radius. The vertical displacement increases with terrain slope and could be above 35 m for a crown radius of 3.5 m and terrain slope of 85°. Unlike a spherical crown, there are no errors in location or height for conical crowns on slopes less than 45°; the crown angle of a conical tree with the location of the treetop and crown radius equivalent to that of a hemi-spherical/spherical tree crown is considered to be 45° (Figs. 7 and 8).

3.4. Discussion

There is increasing interest in the accurate estimation of canopy and individual tree heights in tropical forests for estimating global aboveground carbon stocks. These data are also important for understanding the habitat requirements of species, often on the brink of extinction. Tree height is one of the most important stand characteristics determined in forest inventory (Khosravipour et al., 2015). Most of the algorithms for estimating tree and canopy heights using ALS data, which are currently considered the most accurate, have been developed in boreal or temperate forests which are less complex than tropical forests, with different tree species compositions. The results of this study suggest that the algorithms that have been developed for extracting information from ALS data in other forest types may need to be modified for tropical forests with complex terrain characteristics.

Normalisation using a DTM is an essential step in many tree detection algorithms (Heurich and Weinacker, 2004; Koch et al., 2006). It is possible to vary the search window size for detecting treetops from a CHM, where the search window, representing the crown radius, is expected to increase with tree height (Popescu et al., 2002). For a fixed window size, trees may be over-segmented if the window size is smaller, and may be undetected if the window size is much larger, than

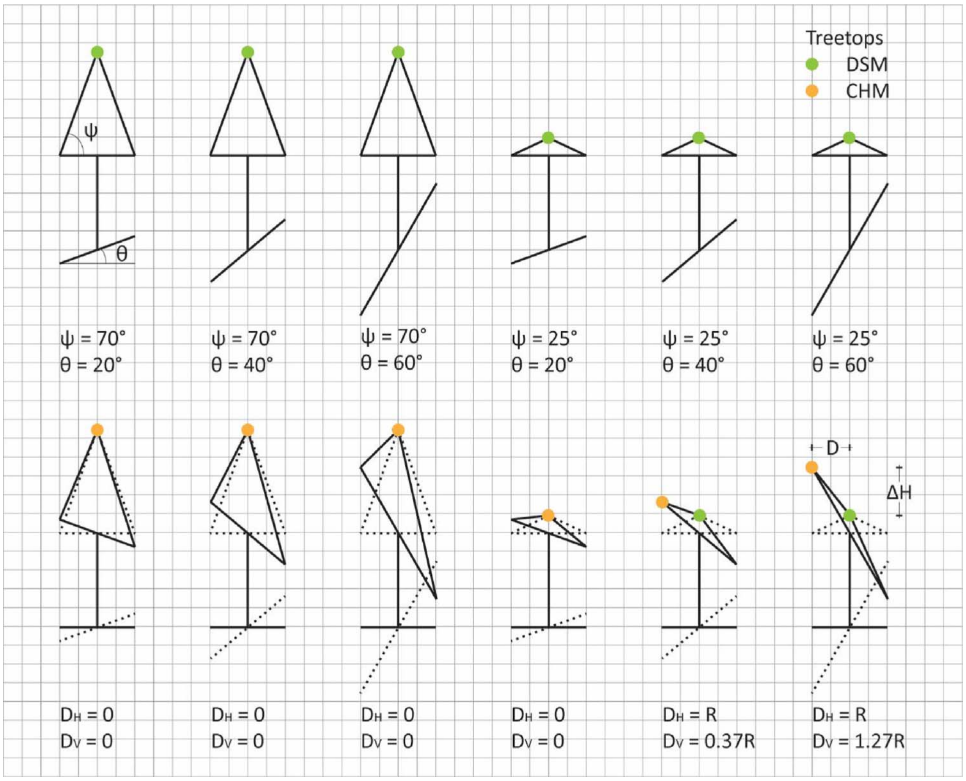

Fig. 5. Potential errors in the locations and heights of detected trees using a Canopy Height Model (CHM) compared to a Digital Surface Model (DSM) based on terrain and crown slopes; $D_V = D_H(\tan\theta - \tan\psi)$, where D_V is the vertical displacement of the treetop after height normalisation, D_H is the horizontal displacement, R is the radius of the tree, θ is the terrain angle and ψ is the crown angle.

the crown radius. The variable window size is therefore a very useful step for delineating individual trees based on a CHM. Despite this advantage, tree delineation based on a DSM has recently been suggested as a better alternative to that based on a CHM due to the potential effect of terrain slope (Khosravipour et al., 2015; Vega et al., 2014). The results of this study support this argument, and this is especially relevant for tropical forests with large trees.

Khosravipour et al. (2015) developed a theoretical model to quantify the systematic error in CHM-based treetop identification for a spherical tree crown. Although it was noted that the displacement of treetops seemed to depend on crown shape in addition to terrain slope and crown radius, it was not directly incorporated in their model: vertical displacement $= r(\sqrt{m^2 + 1} - 1)$, where r is the crown radius and m is the terrain slope, since it was based only on a spherical tree crown. In this study, we attempted to develop a model incorporating crown slope in addition to crown radius and terrain slope based on a conical tree crown. We also developed a model for a spherical tree crown for which our results agree with those of the above study (Khosravipour et al., 2015).

The maximum observed overestimation of tree heights in our study site in a tropical forest, based on CHM, are much higher (16.6 m) than the maximum observed overestimation of 1.78 m in a forest dominated by pine trees. The vertical displacement of mountain pines was found to be less than that of Scots pine trees (Khosravipour et al., 2015). This could be explained by crown slopes rather than crown radii, since errors in the locations of treetops in the horizontal or vertical direction for mountain pines, with an approximate crown angle of 60°, will be negligible for terrain angles less than 60°.

In this study, the detected treetops in $\mathrm{Trees_{DSM}}$ were considered to be more accurate than those in $\mathrm{Trees_{CHM}}$ since the tree crown shape and positions would be maintained in the DSM (Figs. 4 and 5). The tree locations and heights in $\mathrm{Trees_{DSM}}$ were therefore considered to be the actual values, in the absence of field data. Tree stems tend to grow inclined in the downhill direction on slopes, in response to light availability (Lang et al., 2010). This would produce errors in most of the existing tree delineation algorithms where the position of the treetop is assumed to be that of the tree trunk. Although this would affect the estimated tree heights in both $\mathrm{Trees_{DSM}}$ and $\mathrm{Trees_{CHM}}$, it is not expected to have much effect on the estimated differences in tree locations or heights.

A fixed window size of 15 m was used since the aim was only to compare treetop locations and tree heights of $\mathrm{Trees_{CHM}}$ to those of $\mathrm{Trees_{DSM}}$. The selected window size could have resulted in small trees not being detected, but this was not considered to be crucial for this study. Trees shorter than 10 m were excluded to reduce the data volume, and those not within the same crown polygons were excluded to avoid commission errors. The observed overestimation of tree heights using a CHM should therefore be considered to be a conservative estimate. Tree heights do not seem to have any influence on the errors in CHM-based tree locations and heights. The errors will therefore be more pronounced for short trees with large crown radii on steep slopes.

Errors in DTM generated from ALS data are known to increase with slope, and with the density of tree cover (Clark et al., 2004; Su and Bork, 2006). The density of returns have been shown to have a major influence on the accuracy of the generated DTM in tropical forests, with errors ranging from −2.88 m to 4.51 m for a density of 8 returns $\mathrm{m^{-2}}$, although the mean error was only 0.38 m (Leitold et al., 2015). Filtering algorithms for classifying ground points and interpolating these points to generate a DTM could also influence the accuracy of the DTM (Sithole and Vosselman, 2004). Accuracy of the DTM could have influenced the horizontal and vertical displacements of treetops in $\mathrm{Trees_{CHM}}$ compared with $\mathrm{Trees_{DSM}}$. It is also possible that the point density of ground returns of 0.32 returns $\mathrm{m^{-2}}$ may not be sufficient to represent the local micro-topography. However, the optimisation of filtering algorithms is still a research topic in ALS, and was not an objective of this study.

Carbon stock, or above-ground biomass, can be estimated using ALS data based on individual tree heights or canopy heights (Coomes et al., 2017). Study sites are often on flat or gently sloping terrain where existing algorithms based on a CHM can be applied, even in tropical forests (Ferraz et al., 2016; Jucker et al., 2017). However, it may be necessary to take the terrain slope and crown characteristics into

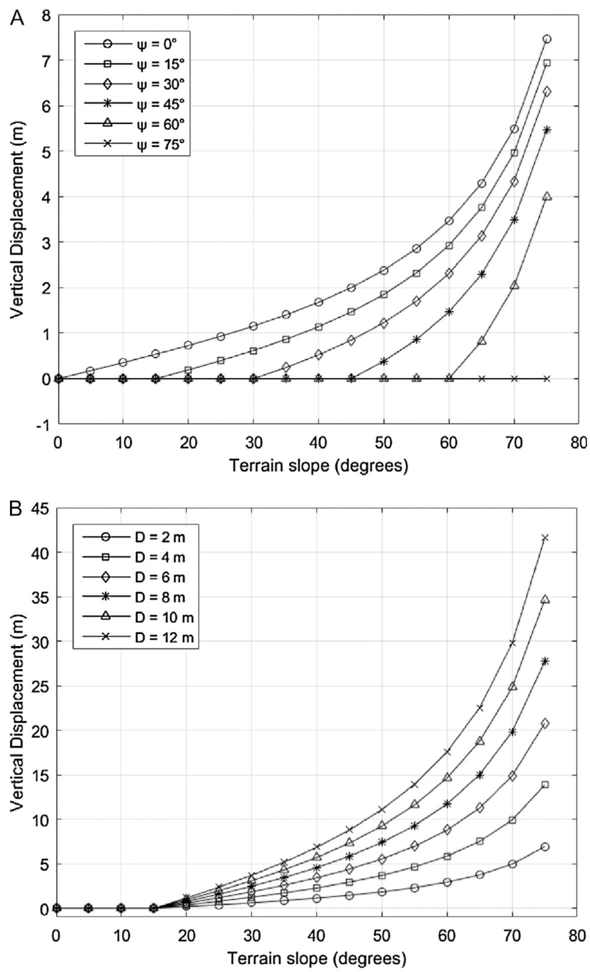

Fig. 6. Modelled vertical displacement for conical tree crowns with crown angles ranging from 0° to 75° at an interval of 15° for a horizontal displacement of 2 m (A); and for a crown angle of 15° with horizontal displacement ranging from 2 m to 12 m at an interval of 2 m (B); $D_V = D_H$ (tan θ-tan ψ), where D_V is the vertical displacement, D_H is the horizontal displacement of the detected treetops, θ is the terrain angle and ψ is the crown angle.

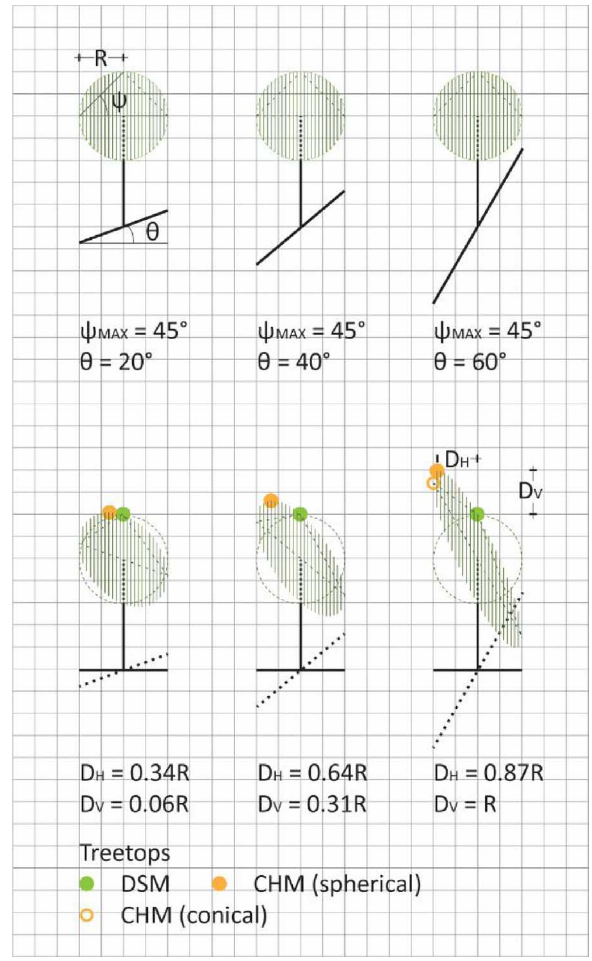

Fig. 7. Potential errors in the locations and heights of detected trees using a Canopy Height Model (CHM) compared to a Digital Surface Model (DSM) based on terrain and crown slopes for a tree with spherical crown (A); DH = Rsin θ; DV = R(sec θ – 1).

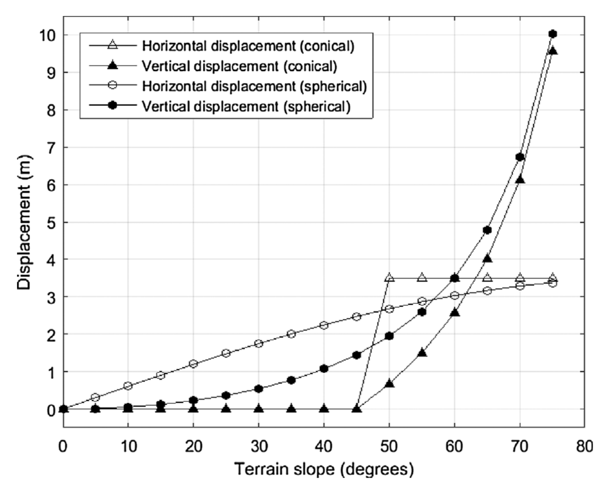

Fig. 8. Modelled horizontal and vertical displacements for a spherical or hemispherical tree crown with a crown radius of 3.5 m, compared to a conical tree crown for the same radius, where the crown angle is considered to be 45°.

consideration for tropical forests on slopes. It should be noted that the ground surface area for a plot on a 60° slope would be twice that of the horizontal surface area, or the area of a similar plot on flat terrain. The tree stem density or canopy volume on a slope could therefore be more than that on flat terrain, with corresponding increase in biomass. It may be possible to predict errors in tree height estimations based on crown radius, terrain slope and crown characteristics. However, more studies are needed to ascertain whether the developed models can be used to correct for slope in biomass estimations.

4. Conclusion

CHMs or height-normalised ALS point clouds are extensively used for delineating individual tree crowns, estimating biomass and carbon stock, and increasingly for habitat quality assessment of species under threat of extinction. Many of the algorithms for extracting information from ALS data for forests have been developed in boreal or temperate forests. These algorithms may have to be modified for trees with large crown radii in tropical forests on sloped terrain. In our study area in Sumatra, the overestimation of tree heights based on a CHM compared to a DSM was much higher, for example, than in a forest dominated by pines in the French Alps (Khosravipour et al., 2015).

This study shows that the error in the estimated height of a tree with a conical crown was influenced by the angle of the crown in addition to crown radius and terrain slope. Therefore, errors occur only when the terrain angle is more than the crown angle. CHMs can therefore be used for tree crown delineation in forests dominated by species such as pines, with steep crown angles as long as the terrain angle is less than the crown angle. There were horizontal displacements, or errors in estimated tree locations, for spherical tree crowns even on gentle slopes. In tropical forests dominated by trees with large crown radii on steep slopes, treetop detection and height estimations based on a DSM could be more accurate than based on a CHM. This in turn would improve biomass estimations in tropical forests based on ALS data, supporting climate change mitigation efforts such as REDD.

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