Supplementary Materials

Mapping Canopy Heights in Dense Tropical Forests Using Low-Cost UAV-Derived Photogrammetric Point Clouds and Machine Learning Approaches

1 DTM Generation Methods Using UAV-DAP Products

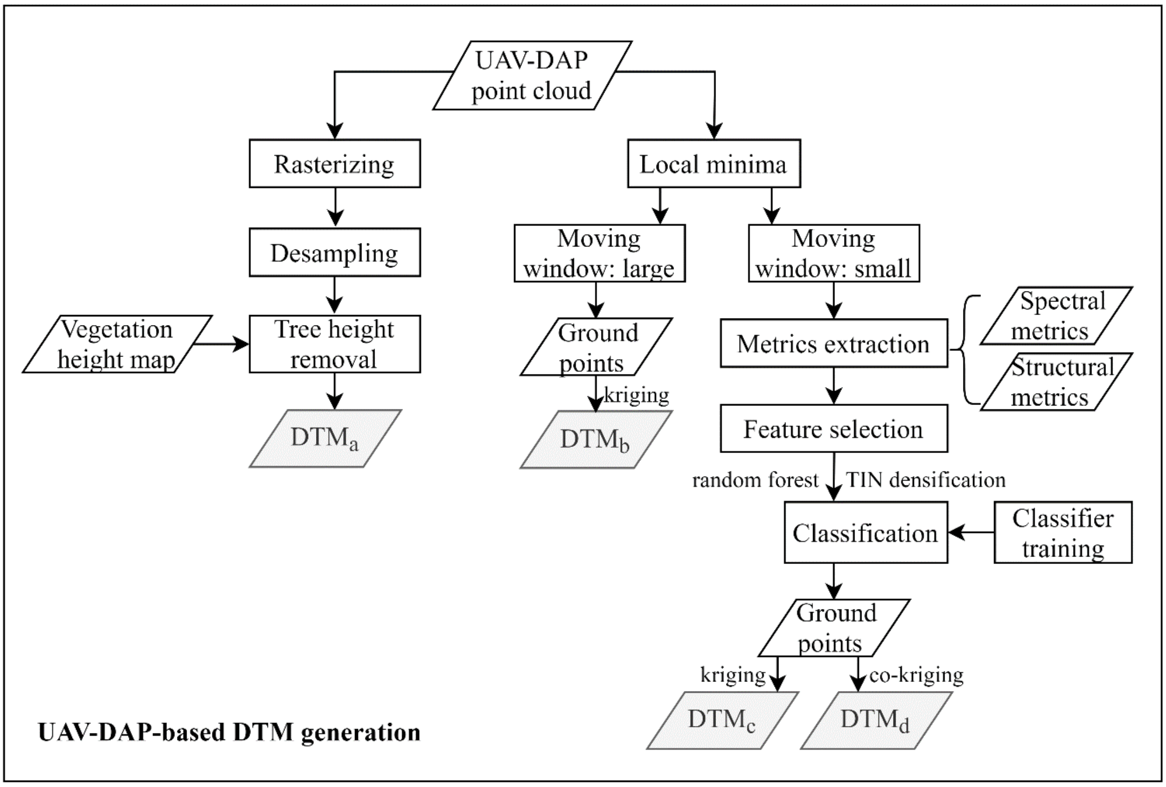

Figure S1. Flowchart of the methodology showing the four processing strategies for UAV-DAP-based DTM generation.

1.1. Method A

This method is the most straightforward and simple method to estimate the underlying terrain and does not involve machine learning. We present it as a basic method to which the more advanced methods can be compared (see below). In this method, the DTM is estimated by subtracting a regional average and representative tree height, inferred from an independent dataset, from a coarse-resolution DSM. The underlying assumption is that the dense canopy is relatively homogeneous at coarser spatial resolution and covaries with terrain. For the DRC, a national vegetation height map is available with a resolution of 100 m (UCLA, WWF, BMUB, KFW, 2017). We desampled the DAP-derived DSM into coarse resolutions (i.e., 5 m, 10 m, 30 m, 50 m, 80 m and 100 m) and assessed their correlation with the reference DTM. After identifying the resolution at which the correlation between reference DTM and DSM was the highest, the mean regional vegetation height was subtracted from this DSM to obtain an estimated DTM (DTM_a; Figure S1). The products described here are referred to as DSM_a, DTM_a and CHM_a in the remainder of the text.

1.2. Method B

In this second method, we use a simple ground filtering method to identify ground points and interpolate these identified ground points to derive the DTM. First, a DEM was constructed by rasterizing the DAP-based point cloud using minimum elevation values of each grid at 0.5 m resolution. We then used local minima as filtering method to select the lowest point in a moving window as a potential ground point. As presented in the main manuscript, the size of moving window affects the number and probability of the points to be the true ground points. In this method, we used a large moving window (radius of 50 m) to detect the local minima for each cell. The rationale behind this approach is that given the large size of the moving window, the selected points would have a high possibility to be ground points. These points are assumed as ground points and interpolated to generate a DTM using original kriging (DTM_b; Figure S1). The products described here are referred to as DSM_b, DTM_b and CHM_b in the remainder of the text.

1.3. Method C

The third method is similar to method B, but here we use a much smaller moving window of 5 m. This substantially increases the number of selected points that are candidates to be true ground points. This approach therefore requires an additional classification procedure to classify the selected minima in true ground points and low points that are understory vegetation (and should not be included in the estimation of the DTM). To this end, we performed a supervised classification using an ensemble learning method based on a set of spectral and structural features derived from the raw DAP-based point cloud. All candidate points within a +/-2 m distance from the true ground, as inferred from the reference ALS-DTM, were considered to be true ground points, while others were regarded as non-ground (i.e., substory). This threshold of 2 m was determined after an analysis of the difference between the DAP cloud and ALS-derived ground points (Figure 7 in the main manuscript). Afterwards, structural features were extracted around these candidate points to contribute to the classification of ground points, including grid density (number of points in each cell), standard deviation of height and height range in each cell (demonstration see Figure A3). These cell-based statistics were performed at grid sizes of 1, 5, 10, 20 and 40 m, respectively. In addition, spectral features of the candidate points were extracted from both the top and bottom layer of the cloud, including their R-, G- and B-band values, as well as YUV values (a brightness index). Considering possible changes in light conditions during data collection, we included only their normalized values into analysis, i.e., subtracting the mean and dividing by the standard deviation. As such, each value would reflect the distance from the mean in units of standard deviation. In total, 23 variables were extracted into the exploratory analyses to determine their importance and construct the classification model. A random forest (RF) classification was applied to classify the candidate points into ground or non-ground points. A subset area of the Yangambi site was used for model calibration. As an exploratory method, it provides information on whether variables are important or not in the classification, which gives directions for final model calibration. We validate the performance of the developed classification model by applying it on the area not used for model calibration and evaluate the estimated DTM by comparing it to the reference DTM. The accuracy of the RF classification was estimated by using the proportion of correct predictions among the total points. The feature importance of the predicting model was also derived for exploratory analysis (Figure A3). The classifier training and assessment were performed in R (Version 3.5.1, R Core Team). In the next step, we performed a geometry-based filter, i.e., TIN densification filtering algorithm, to further screen ground points. The algorithm first generates a sparse TIN through seed points (the original term from the paper, similar with "candidate points" in this case by definition) and then iteratively processes layer-by-layer densification until all ground points have been classified. The iterations traverse all the unclassified points, query the triangles that each point belongs to in the horizontal projection plane and calculate the distance (d) from the point to the triangle and the maximum angle between the point and three vertices with the triangle plane. The distance and maximum angle are compared with the threshold values to determine the classification and to repeat this process until all ground points have been classified (Zhao et al., 2016). This procedure was performed using the LiDAR360 software (GreenValley Ltd.). These resulting selections of points are then very likely to be ground points that can be used for interpolation. Finally, the DTM was generated by interpolating the filtered ground points using original kriging (DTM_c; Figure S1). The products described here are referred to as DSM_c, DTM_c and CHM_c in the remainder of the text.

1.4. Method D

This solution is a slightly modified version in terms of the interpolation method based on the former method C. Instead of using ordinary kriging, we applied a co-kriging technique, i.e., kriging with external drift (KED), where the aforementioned coarse-DSM was used as a co-variable to assist in the interpolation (DTM_d; Figure S1). The rationale is that the DSM contains information on the underlying topography and can thus improve the interpolation, particularly in regions where limited amounts of ground points are detected. This method also allows to create a prediction standard error map. The interpolation was performed in ArcMap 10.4 (ESRI). The products described here are referred to as DSM_d, DTM_d and CHM_d in the remainder of the text.

2. DTM Generation Results Using UAV-DAP Products

A comparison of DTMs generated from the four methods is shown in Figure S2. DTM_a showed a less accurate result with an RMSE of 4.58 m and an NSE of 0.53. DTM_b using a large moving window resulted in an underestimation locally. This indicated that the density of points for interpolation was not high enough to retrieve the terrain details. DTM_c, on the other hand, utilized small moving window for the detection of minima points and the RF+TIN classifier well identified ground points, resulting in an improved performance with an RMSE of 2.25 m and an NSE of 0.878. Compared with DTM_c, the DTM_d using co-kriging showed better performance. In summary, among the four DTM generation approaches, the small moving window along with co-kriging (DTM_d) showed the best reconstruction (RMSE = 2.1 m, NSE = 0.894), and this method was finally reported in the main manuscript.

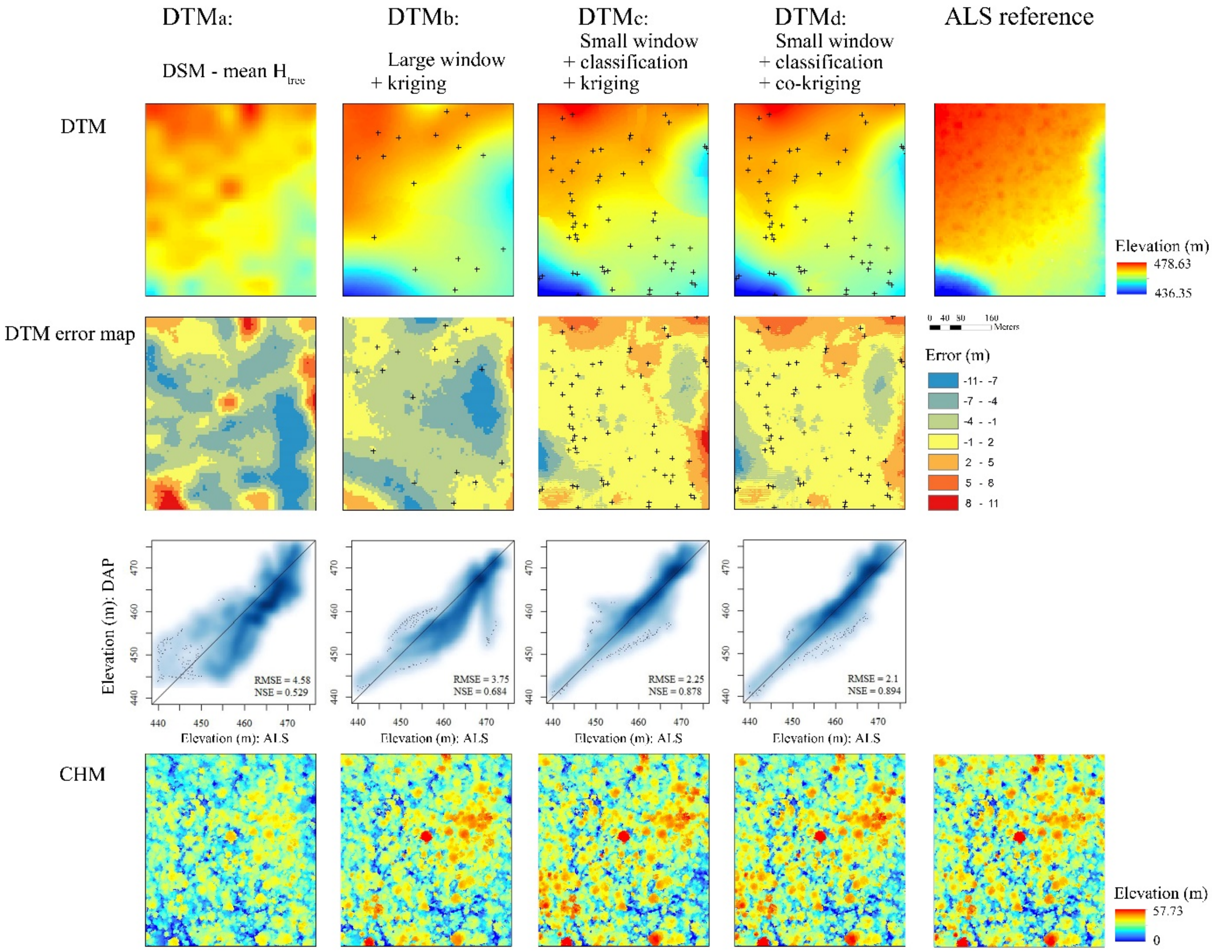

Figure S2: Comparison of DAP-based outputs and the ALS reference. Top: DTMs generated using DAP-based methods and the reference ALS DTM. The black marks depict the points that were classified as ground. Middle: Difference map between DAP-derived DTMs and the reference ALS DTM and their comparison of elevation values of each grid. Bottom: CHMs generated using DAP-based methods and the ALS reference.