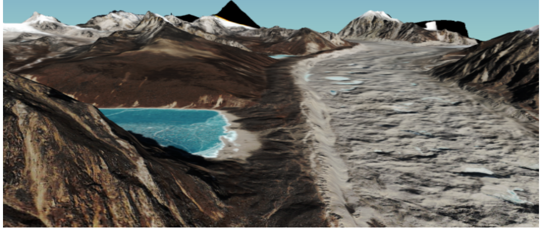

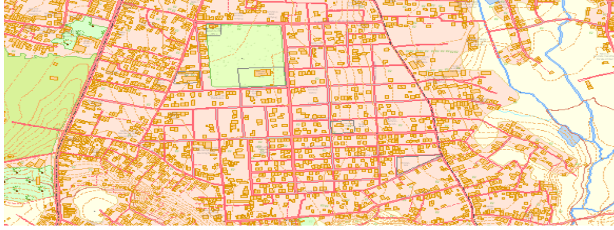

Feasibility Study and Prototype Development on Use of UAS on Forest Monitoring and Forest Crime Control in Karnali Province

(Program Reference Number: 07/2078/079)

Final Report

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Abbreviations

CCSP	Concentric Circular Sample Plots
CFUG	Community Forest Users' Group
CHM	Canopy Height Model
CV	Curriculum Vitae
dBH	Diameter at breast height
DFO	District Forest Offices
DGPS	Differential GPS
DNPWC	Department of National Parks and Wildlife Conservation
DoFSC	Department of Forests and Soil Conservation
DSM	Digital Surface Model
FCS	Forest Canopy Structure
FRA	Forest Resources Assessment
FRTC	Forest Research and Training Centre
GCP	Ground Control Points
GNSS	Global Navigation Satellite System
ICP	Independent Check Points
LRP	Local Resource Person
MoFE	Ministry of Forests and Environment
MoITFE	Ministry of Industry, Tourism, Forests and Environment
NDVI	Normalized Difference Vegetation Index
NFI	National Forest Inventory
PSP	Permanent Sample Plots
REDD	Reducing Emissions from Deforestation and Forest Degradation
RTK	Real Time Kinematics
TLS	Terrestrial Laser Scan
UAS	Unmanned Aerial System
UAV	Unmanned Aerial Vehicle

Executive Summary

Unmanned Aerial Vehicle/System (UAS/UAS) commonly known as "drone", with highly accurate calibrated imaging multi-spectral sensors, nadir and oblique imaging capability, highly robust deployment for both aerial photography and videography provides opportunities for rapid monitoring and support for measurement of stand level forest data. UAS can also provide a practical and robust solution for rapid monitoring of forest disturbances including forest fire. These capabilities of UAS has provided opportunity for monitoring and assessment of forest resources in very challenging conditions and difficult terrain of resource rich Karnali Province. With an aim to test and assess the applicability of modern technology using UAS for scientific forest inventory and monitoring, Forest Research and Training Centre (FRTC), Karnali Province, has undertaken this research to develop prototype through a feasibility study of UAS based approach for forest monitoring in the province.

UAS based scientific forest inventory was undertaken in 64 plots in existing 22 National Forest Inventory (NFI) clusters covering Siwalik, Middle Mountain, High Mountain and High Himal Physiographic regions in Karnali Province. High accurate DJI P4 MSS Agriculture UAS with D-RTK2 GNSS positioning system was operated in 42 NFI plots with addition of 22 UAS plots to capture 10cm resolution stereo imagery data. The imagery was captured in 100m x 100m inventory plots circumscribing the NFI CCSPs. Field level inventory was undertaken in the established 22 UAV plots (center plot of 300m x 300m NIF cluster) to supplement the UAS captured data, following FRTC field inventory protocol.

Standard FRA/NFI CCSP was established at the center of UAV plot (coinciding with the center of NFI cluster), which is an addition to already established six FRA/NFI CCSPs in each cluster. Trees within the sample plot were measured based on the guidelines of field manual, FRTC. Field inventory data was filled in standard Tally Sheet and entered into database system immediately after the completion of the plot measurement. The recorded and entered data was validated by the inventory crew leaders (Forest Technicians) for consistency and accuracy.

Canopy Height model (CHM) was obtained by deducting Digital terrain model from Digital surface model. CHM were further processed using 3*3 gausian filter to prevent formation of multiple local maxima. Individual tree crown was detected using multi-resolution segmentation and watershed transformation algorithms. For this, CHM band was weighted thrice the multispectral bands.

Regression model was used to describe the nature of relationship between variables- height derived from UAV (CHM) and tree height measured from field; canopy projection area derived from UAV (CPA) and height measured from field; CHM and canopy projection area (CPA); above ground biomass (AGB) and CHM and CPA . To test the significance of the regression, F statistics and T statistics were studied using null and alternate hypothesis.

Regression analysis between CHM generated from UAV and field height showed higher r^2 (0.7) for overall tree species. *Pinus roxbhurghii* had lower r^2 (0.37) compared to *Shorea robusta, Buchanania latifolia and Terminalia alata* (above 0.6). T and F statistics also showed significant relation between CHM and field height for all species at 95% confidence level.

Regression analysis between CPA and tree height showed higher r^2 (0.78) for overall tree species. *Shorea robusta and Terminalia alata* had higher r^2 (above 0.5) compared to *Pinus roxbhurghii and Buchanania latifolia* (below 0.2). T and F statistics showed significant relation between CPA and field height for *Shorea robusta, Pinus roxbhurghii and and Terminalia alata* at 95% confidence level.

Regression analysis between CHM and CPA showed higher r^2 (0.52) for overall tree species. *Shorea robusta, and Terminalia alatan* had higher r2 (above 0.5) compared *Pinus roxbhurghii*

and Buchanania latifolia (less than 0.04). T and F statistics showed significant relation between CHM and CPA for *Shorea robusta, and Terminalia alata* only at 95% confidence level.

Regression analysis between AGB, CPA and CHM showed r^2 of 0.36 for overall tree species. *Shorea robusta* had higher r^2 (above 0.5), while *Pinus roxbhurghii, Buchanania latifolia and Terminalia alata,* had low r^2. T and F statistics showed significant relation between AGB, CHM and CPA for *Shorea robusta* only at confidence interval of 95%.

The study demonstrated technical feasibility of the approach, however, conditionally and under a controlled environment with availability of ample time to compensate for various environment and physical conditions. The main challenges and constraining factors were the terrain in the study sites, accessibility, weather conditions during UAS operations and other factors such as internet access (required for RTK processing), limitations of used UAS equipment were major factors that contributed to technical limitations. Other technical limitations included issues in Point Cloud Generation and Classification due to varying light conditions while acquiring imagery data at different time of day, variable flight height due to terrain and forest canopy structure restricting accurate DEM generation; tree crown delineation due to overlapping of the grown in mixed forest types.

For scientific study of UAS based forest inventory in terrain conditions analogous to Nepal following recommendations are made:

- UAS operating in "visual line-of-sight (VLOS)" is deemed not very suitable. UAS that operates in "beyond visual line of sight (BVLOS)" with longer operating time is suitable.
- Base point/control point markers should be established clearly while operating the UAS for higher accuracy.
- Cross-flight configuration at different heights will capture images from different angle, which will minimize occlusions in certain degree.
- Crown diameter of each tree along with crown overlapping percentage should be noted in the field.
- Photograph of the tree crown should also be taken so that tree crown overlapping pattern can be identified for accuracy assessment.
- Inventory tally trees for sampling (image training) should be located using high precision GNSS system in compliance to the GNSS system used in RTK based UAS.
- UAS survey and trees location measurement should be done from the same GNSS base station in a plot.

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1. INTRODUCTION

1.1. Background

Frequent and detailed updates about forest are essential for effective management of Forest. Monitoring of forest through ground based physical observations/measurements is labour and resources intensive. Monitoring and measurement of forests in steep hill slopes and in mountainous terrain is impractical due to inaccessibility and risks to the field crew, making such missions impracticable, as in the landscape of Karnali Province. Very high resolution satellite imagery based multi-source forest inventory, mid-resolution imagery based satellite land monitoring system (SLMS) are very widely used of large scale national/sub-national forest inventories (NFI) and continuous forest monitoring for REDD+ MRV purposes. However, these approaches are, in general adopted to support large scale forest inventories and land use land use change (LULUC) assessments, which still requires significant ground based field inventories of the forest sample plots. Further, the ground. Ground Sample Density (GSD) of the very high resolution (commercial) imagery data (≈0.5m), terrain effects, limitations during cloud cover, lag time for data acquisition, processing and the cost factor limits the use of such data to certain degree.

With the recent development and ubiquitous use of Unmanned Aerial Vehicle/System (UAS/UAS)[1] with highly accurate calibrated imaging multi-spectral sensors, nadir and oblique imaging capability, highly robust deployment for both aerial photography and videography provides opportunities for rapid monitoring and support for measurement of stand level forest data. Stereo imaging capability supports digital photogrammetry and computer vision based Structure from Motion (SfM) analysis to create digital 3D model of the forest canopy structure. Airborne Laser Sensor (ALS or LiDAR) payload mounted UAS is capable to capture 3D dense point cloud for very accurate 3D modelling of forest stand to support accurate volume and biomass estimation.

UAS can also provide a practical and robust solution for rapid monitoring of forest disturbances including forest fire. Several forests related problems such as forest fire, wildlife crime can be reduced through the use of UAS (Skorput et al., 2016)based monitoring. Further, UAS has been identified effective tool for forest mapping, as both the spatial and temporal resolution of UAS imagery better suit local-scale investigation than traditional remote sensing tools (Lisein et al., 2013).

Karnali Province is one of the least developed regions in the country with HDI of 0.538, which is lower than the national average of 0.587, but is endowed with rich natural resources. Forest is primarily the major sources for sustaining the livelihood of the population in the province. Due to very high and difficult terrain, arable lands are limited and fragmented, high altitude pasture land are much less used due to the climatic harshness. Forest and forest based non-timber forestry products (NTFPs) including Medicinal and Aromatic Plants (MAPS) value chain and eco-tourism are the possible resources that can enhance the GDP of the province.

The dependency of people primarily on forest has posed threat to forest as forest disturbances and related crimes has increased. Illegal felling of trees, deliberate forest fire, encroachment of forest land is increasing. Extreme heat, dry and drought like conditions due to climate change impacts has exacerbated occurrences of forest fires and the extent covering larger areas.

[1] Now termed as "Uncrewed Aircraft System (UAS)" comprising of an Unmanned Aerial Vehicle (UAS or commonly drone), ground control (person controlling the UAS flight) and the system (mission planning and control hardware and software) that connects both the UAS and controller. For consistency, the term "UAS" is used in the document throughout referring to the "Uncrewed Aircraft System".

In this context, continuous monitoring of forests in Karnali Province is rather very challenging due to terrain, remoteness, road inaccessibility as well as limitations of fiscal and human resources with the concerned agency. In this context, the traditional approach of forest monitoring to support sustainable forest management will need to be replaced using modern and innovative technologies.

With an aim to test and assess the applicability of modern technology using UAS for scientific forest inventory and monitoring, Forest Research and Training Centre (FRTC), Karnali Province, has undertaken this research to develop prototype through a feasibility study of UAS based approach for forest monitoring in the province. Further, this study aims to recommend suitable light weight UAS for forest monitoring (including encroachment detection, forest fire monitoring, forest crime monitoring and Forest inventory) in Karnali Province.

1.2. Objectives and Scope of Work

The main objective of this assignment was to “develop a prototype on use of small UAS in forest monitoring in Karnali Province” in all geographic regions of Nepal. Under this overarching objective, specific objectives were:

- To assess the feasibility of using Multi-spectral sensor UAS inventory and mapping of forest growth as well as collect high resolution aerial photographs for mapping three-dimensional (3D) forest canopy structure in Karnali province.
- To assess the feasibility of using multi-spectral sensor UASs in monitoring of forest fire and forest crime.
- To create the Forest Canopy Height Model from multi-spectral UAS imagery.
- To assess the extent to which UAS-derived canopy attributes contribute to our understanding of local-scale patterns in biodiversity and biomass storage.
- Comparison of traditional technique and Modern technique (using UAS) for forest inventory.
- Modelling of forest growth for future management of forest.

1.3. Study Area

The study sample plots were distributed throughout geographic area of Karnali Province (except Humla and Dolpa districts) with an area of 30,211 km^2 to cover physiographic regions of Siwalik, Middle Mountain, High Mountain and High Himal.

There are 204 existing NFI plots (FRA inventory and additional plots) established by FRTC during FRA-Nepal Projects and subsequent re-measurement and additional measurement missions. From these NFI plots, UAS data was captured in 64 plot in 22 NFI clusters, including 22 UAV plots established to undertake NFI inventory and UAS data acquisition for the study.

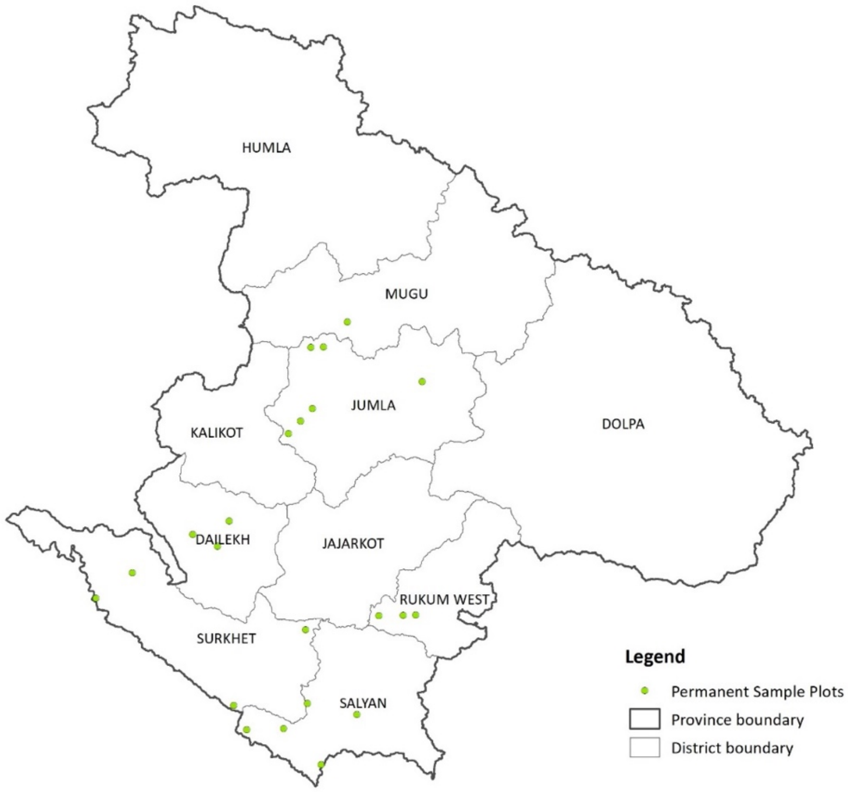

Figure 1 NFI plots (FRA plots and additional plots) (Source: FRTC 2010-2021)

1.4. Limitation of the Study

Undertaking of this novel study encountered several limitations in the field, data generation and analysis. The terrain in the study sites, accessibility, weather conditions during UAS operations and other factors such as internet access (required for RTK processing), limitations of used UAS equipment were major factors that contributed to technical limitations. Following were the major limitations encountered during the study:

1.4.1. Landscape and Terrain

- Due to very undulated and steep terrain at the locations of the NFI plots and UAS plots, the flight missions at the constant height (80-200m from the ground) were not able adequately capture vertical images of the canopy in the middle and lower slopes. The canopy of the upper slope obscured the lower canopy causing occlusions in the images; hence the DSM/DEM of such occlusion area could not be generated properly to develop reliable canopy height and structure models.
- Similarly, the high variability of terrain resulted in uneven pixel distributions in each plot which affected the quality of images.

1.4.2. Mission Planning and Observation Timing

- Though the UAS and inventory missions for each plot were rigorously planned using high resolution satellite images, (Google Earth), prior field knowledge of the locations and environment of the NFI plots and local knowledge, undertaking UAS surveys needed micro planning for each plot at the site. The steep terrain, non-availability of internet connectivity, wind and weather conditions played vital role in successfully undertaking UAS mission in each plots.

- Mission planning with fixed schedule might not always be practical as repeated flights were required in certain cases due to technical issues in UAS equipment, weather and wind condition.
- The major limitation of UAS under 2kg operating with visual line of sight is the non-availability of visual line of sight in sloping terrain of Siwaliks; and highly sloping terrain of Middle Mountains and High Mountains.
- Undertaking the mission during the months of February-May also posed limitations in these regions due to leaf-off period of dominant species during February-April and regeneration period during April-May. The period between mid-August to November is deemed suitable period for such studies.
- Due to operation of the UAS during evening, low light conditions and surface illumination resulted in shadow conditions in several plots, which effected the generation of point cloud and DSM.

1.4.3. Equipment Limitation

- UAS equipment used is highly advance DJI P4 Multispectral Agriculture UAS with D-RTK2 GNSS developed with primary function of monitoring agriculture crops over large flat area. The MSS sensor is primarily used for deriving vegetation indices in-the-fly to monitor the health of the crops in "precision agriculture". However, this equipment has been successfully used in monoculture forest monitoring in relatively flatter regions. Though the MSS sensor and RTK GNSS provide better understanding and accuracy, the use in diversified forest in hilly and mountainous terrains have significant limitations.
- The UAS equipment used do not have thermal imaging sensor, hence the detection of forest fire under canopy has severe limitations. Forest fire could be "observed" only using the VNIR sensors.
- The GNSS RTK required establishing of RTK base station with relatively fast internet connectivity in the vicinity of the plot. However, due to the terrain conditions and lack/limited internet connectivity connection between the RTK station and UAS could not be established properly in several plots. Due to this the accuracy of the image data was compromised. Ground markers could be established in flatter areas, however due to terrain and canopy such markers were not practical to be established in the plot locations to obtain better accuracy. The UAS required continuous communication with the RTK stations throughout the mission, which was not achieved in several plots.

1.4.4. Technical Limitation

Point Cloud Generation and Classification

- Due to the issue of occlusion in the images (refer 1.4.1), point cloud could not be properly generated. Consequently, classification of point cloud encountered voids or very limited points, which limited the DSM generation.

Flight Height and DEM Generation

- Flight height influence the accuracy of generated DEM. Accuracy of generated DEM decreases with increasing flight height (Abou Chakra, Somma, Gascoin, Fanise, & Drapeau, 2020; Nguyen et al., 2020). Flight altitude below 100 m provides better accuracy and coverage compared to higher flight altitudes (Abou Chakra et al., 2020). UAS flight in the study ranged from 80 to above 200 m, considering the mountainous terrain and tree height. This can influence the accuracy of DEM and DSM, which in turn can affect the accuracy of

CHM. Also, DEM generated in flat areas relatively have higher accuracy compared to DEM generated in sloppy terrain affecting the accuracy of CHM (Fuad et al., 2018; Jiménez-Jiménez, Ojeda-Bustamante, Marcial-Pablo, & Enciso, 2021).

Tree Crown Delineation

- Tree crown delineation is highly affected by forest stand characteristics such as stand density, species heterogeneity, and stands age (Mojdeh Miraki et al., 2021). In mixed broadleaved forest, it is hard to delineate individual tree crown, where tree crown overlap each other.

1.4.5. Issues in Locating Inventory Trees

- The inventory of the trees in the UAS plots followed the NFI protocol, which required locating of the tallied trees using compass and measuring tape to record the bearing and distance respectively with reference to the center of the plot. The center of the plot is located using a handheld GPS with positional accuracy of 10-30m. Both these methods significantly reduced the accuracy and is not comparable with the RTK based UAS images. Hence the trees located on the ground in the inventory could not be exactly matched with the corresponding trees in the UAS images. This significantly created errors in developing CHM, canopy and other models. Due to this issue, the coordinates of trees in selected 6 UAS plots were re-measured using dual frequency GNSS with RTK such that high positional accuracy is achieved to match with corresponding trees in UAS imagery.

Consideration all these technical and other limitations, the study aimed to pilot the applicability of this novel approach with mixed results. The following chapter presented the method and results and critically discusses the outcomes with practical recommendations for further considerations and provides a pathway for similar studies.

2. METHODOLOGY

2.1. Research Design

The research was design in close consultation with FRTC Karnali to conduct simultaneous UAS based forest inventory plot imagery data capture along with forest inventory data collection following the NFI/FRA approach. The UAS flight missions were planned to be undertaken in the NFI forest clusters and plots established by the FRA-Nepal project (2010-2015) and additional measurement plots undertaken by FRTC during 2018-2022 in Karnali Province. Additional plots were established in the NFI clusters for the purpose of field inventory to support the UAS based inventory.

2.2. Plot Layout

NFI plots design were used as the basis for UAS plot design. UAS data were captured in 100m x 100m plots around the available 6 NFI plots, with addition of the 7th plot at the center of the NFI cluster as shown in Figure 2.

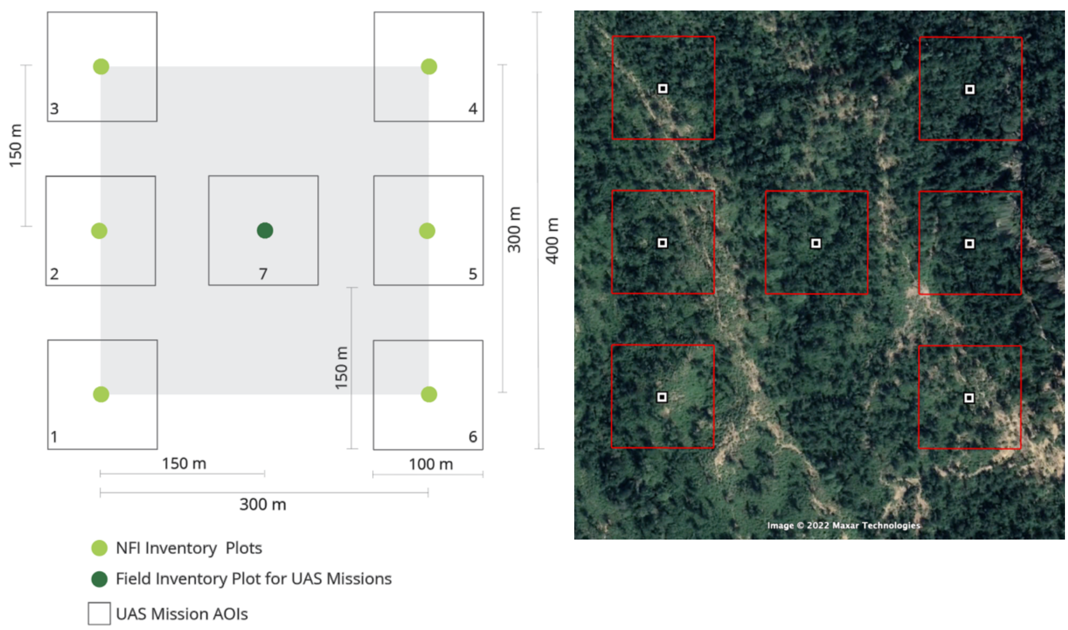

Figure 2 NFI plots and UAS plot layout

2.3. UAS Equipment and Sensor

UAS flight mission were undertaken using newly acquired DJI P4 Multispectral Agriculture UAS with D-RTK2 GNSS station acquired by the FRTC Karnali. MSS sensor available with DJI P4 MSS Agriculture UAS has specifications as listed in Table 1.

Table 1 Specification of Multi-Spectral Sensor (MSS) Array

Sensor	Wavelength (nm)
Blue (B)	450 nm ± 16 nm
Green (G)	560 nm ± 16 nm
Red (R)	650 nm ± 16 nm

Red Edge(RE)	730 nm ± 16 nm
Near Infrared (NIR)	840 nm ± 26 nm

Source: https://www.dji.com/p4-multispectral/specs

Table 2 GNSS RTK Specification

GNSS	Specification
Single-Frequency High-Sensitivity GNSS	Single-Frequency High-Sensitivity GNSS GPS + BeiDou + Galileo[2] (Asia); GPS + GLONASS + Galileo[2] (other regions)
Multi-Frequency Multi-System High-Precision RTK GNSS	Frequency Used GPS: L1/L2; GLONASS: L1/L2; BeiDou: B1/B2; Galileo[2]: E1/E5 First-Fixed Time: < 50 s Positioning Accuracy: Vertical 1.5 cm + 1 ppm (RMS); Horizontal 1 cm + 1 ppm (RMS). 1 ppm indicates error with a 1 mm increase over 1 km of movement. Velocity Accuracy: 0.03 m/s

Source: https://www.dji.com/p4-multispectral/specs

Figure 3 DJI Phantom4 Multispectral Quadcopter platform (UAV) and multispectral sensor payload (Source: https://www.dji.com/p4-multispectral)

2.4. UAS Flight Missions

UAS flight missions were conducted in 64 numbers of 100m x 100m UAS plots to capture stereo imagery data at a predefined flying height (sample shown Figure 5). UAS flight missions were undertaken with proper authorization obtained from MoITFE, Karnali Province, Ministry of Home Affairs and Civil Aviation Authority of Nepal (CAAN) and necessary coordination with district Administration Offices and security agencies.

Due to non-availability of direct visual line of sight from the position of flight operator due to very steep and difficult terrain, UAS flight mission configurations for each plot have to be planned in the field and undertake accordingly. The configuration of the flight also depended on the flight time of 25 minutes with a full charged battery set onboard. Several flight missions were needed to be undertaken to cover all the seven forest plots in a cluster. For the clusters with lower number of forested plots, the flight mission were undertaken to cover those plots only.

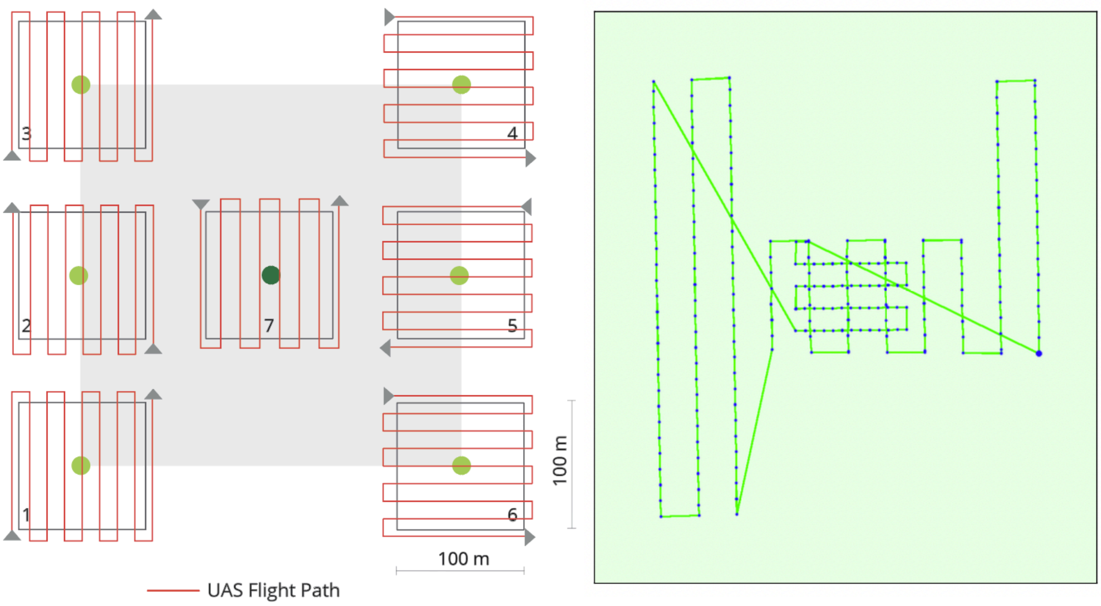

Figure 4 Typical UAS flight mission configuration (left) and actual flight mission path in cluster 32-74 (right)

The flight mission path were planned with optimal flight duration and plot conditions – forested, terrain, obstacles, location of RTK station, wind conditions, safety measures etc. The mission planning was done in-situ using DJI GS Pro (IOS App) using IPad Mini. Independent of flight configurations, the images were processed to generate seamless ortho-mosaics and Digital Surface Model (DSM) extracted from the stereo images as shown in Figure 5.

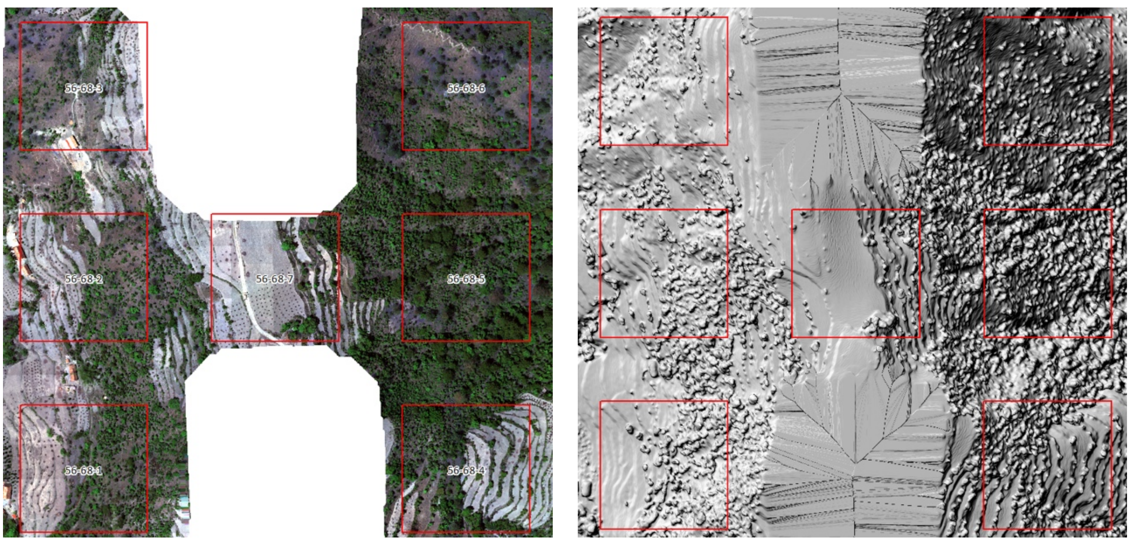

Figure 5 UAS captured imagery data (left) and extracted DSM (right)

GNSS Real Time Kinematic (RTK) station was established in an appropriate location within 500m of the plots and linked with the DJI UAV

In general, the flight missions were conducted as:

Flight Parameters	Specs
Flight platform	Rotary wing (quad copter) – DJI P4 MSS Agriculture UAS with D-RTK2 and/or Autle Pro II
Flight Height (Single path)	70m above ground (uniform height)
Flight Height (Cross path)	70m (same height) and/or 80-100m above ground
Flight Speed	18-20 m/sec (30 fps)
Oblique Flight Height	80-100m above ground
Camera tilt angle	40^{o}
Panchromatic (PAN)	Visible light (RGB)
Ground Sample Density (GSD)	5-8 cm
Forward Overlap	80%
Side Overlap	60%
Image format	JPEG + TIFF (MSS)

2.5. Field Inventory of Plots

Standard FRA/NFI CCSP were established at the center of UAS plot (Plot 7 coinciding with the center of NFI cluster) as shown in Figure 2. This plot is in addition to already established six FRA/NFI CCSPs in each cluster. Trees within the sample plot were measured as:

- trees having 30cm DBH or more enumerated within a 20m radius plot (area: 1256.6 m^2)
- trees having 20-29.9cm DBH enumerated within a 15m radius plot (area:706.9 m^2)
- trees having 10-19.9cm DBH enumerated within a 8m radius plot (area:201.0 m^2)
- trees having 5-9.9cm DBH enumerated within a 4m radius plot (area: 50.3 m^2)
- Every 5^{th} tree height using Vertex
- Measurement of DBH of trees with height >5m

Several supplementary sub-plots will be established (Sample Type 2) to measure seedlings, saplings and poles to monitor the forest growth. The crown density of the forest stand were measured using Densiometer. This enable to correlate canopy structure from the image to the ground based measurement of canopy closure to parametrize the forest canopy structure (FCS).

Field inventory data were filled in standard Tally Sheet and entered into database system immediately after the completion of the plot measurement. The recorded and entered data were validated by the inventory crew leaders (Forest Technicians) for consistency and accuracy.

2.6. Data Processing

The UAS image data were processed using professional software Pix4d Mapper for photogrammetric processing of the images and to generate ortho-photo mosaics and dense 3D point cloud using SfM algorithm. The 3D point cloud were further processed and analyzed by segmentation algorithm to classify canopy structure, calculate tree dBH, height and volumes using open source software 3D Forest (https://www.3dforest.eu/) specifically used for forest 3D modelling and analysis. 3D forest canopy structure (FCS) and canopy height model (CHM) were generated using specialized algorithm in the software.

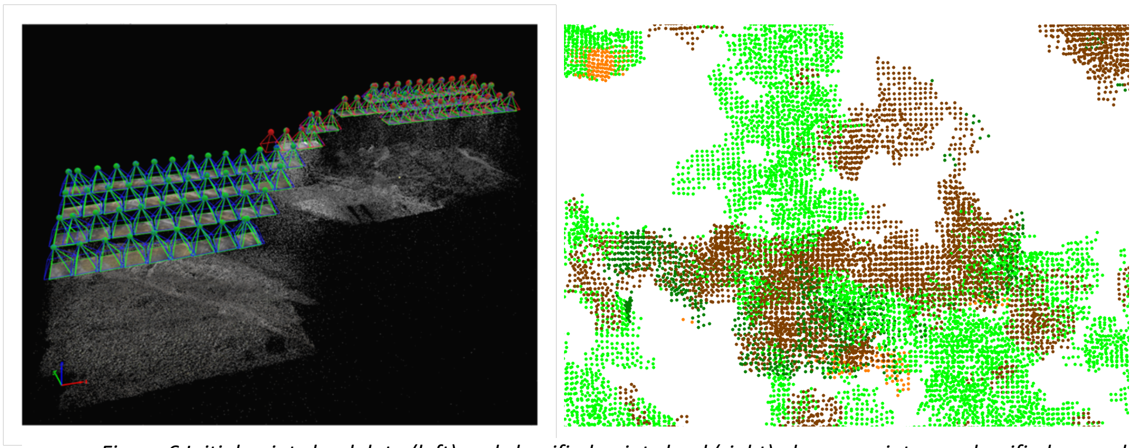

Figure 6 Initial point cloud data (left) and classified point cloud (right) - brown points are classified ground and green as vegetation

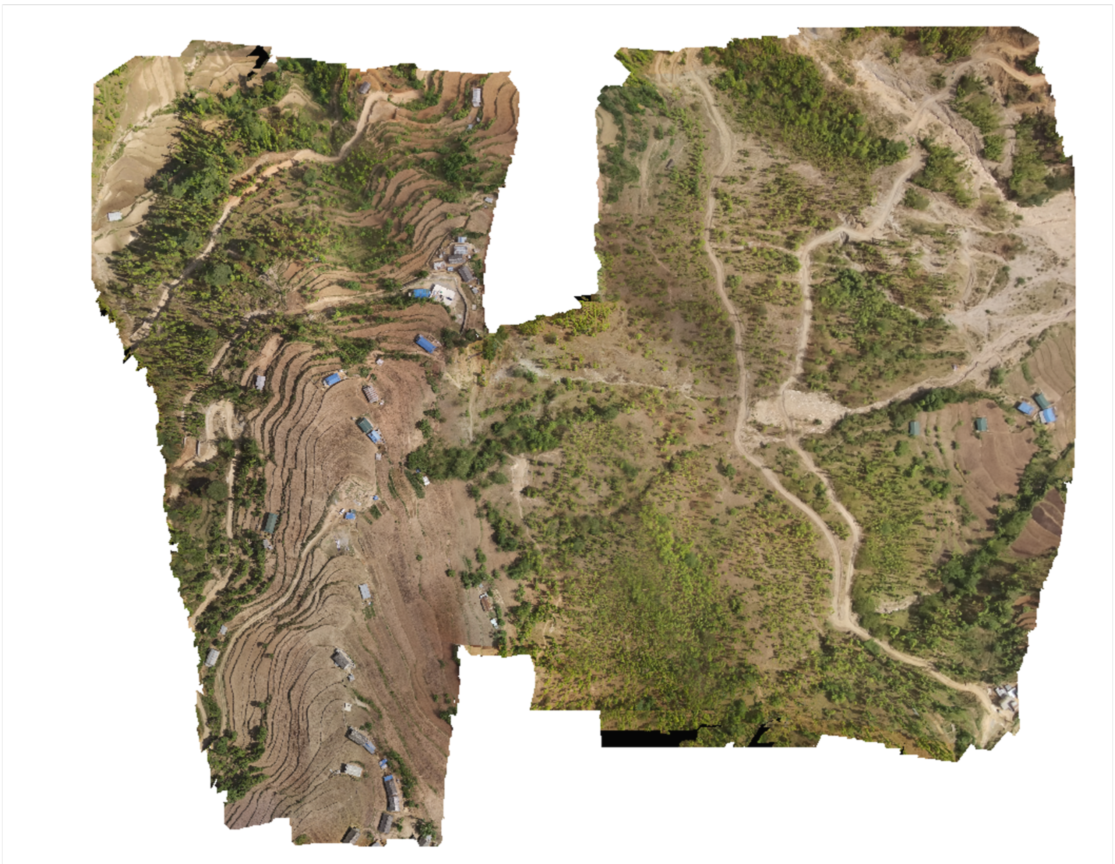

Figure 7 RGB mosaic orthophoto of cluster 32-74

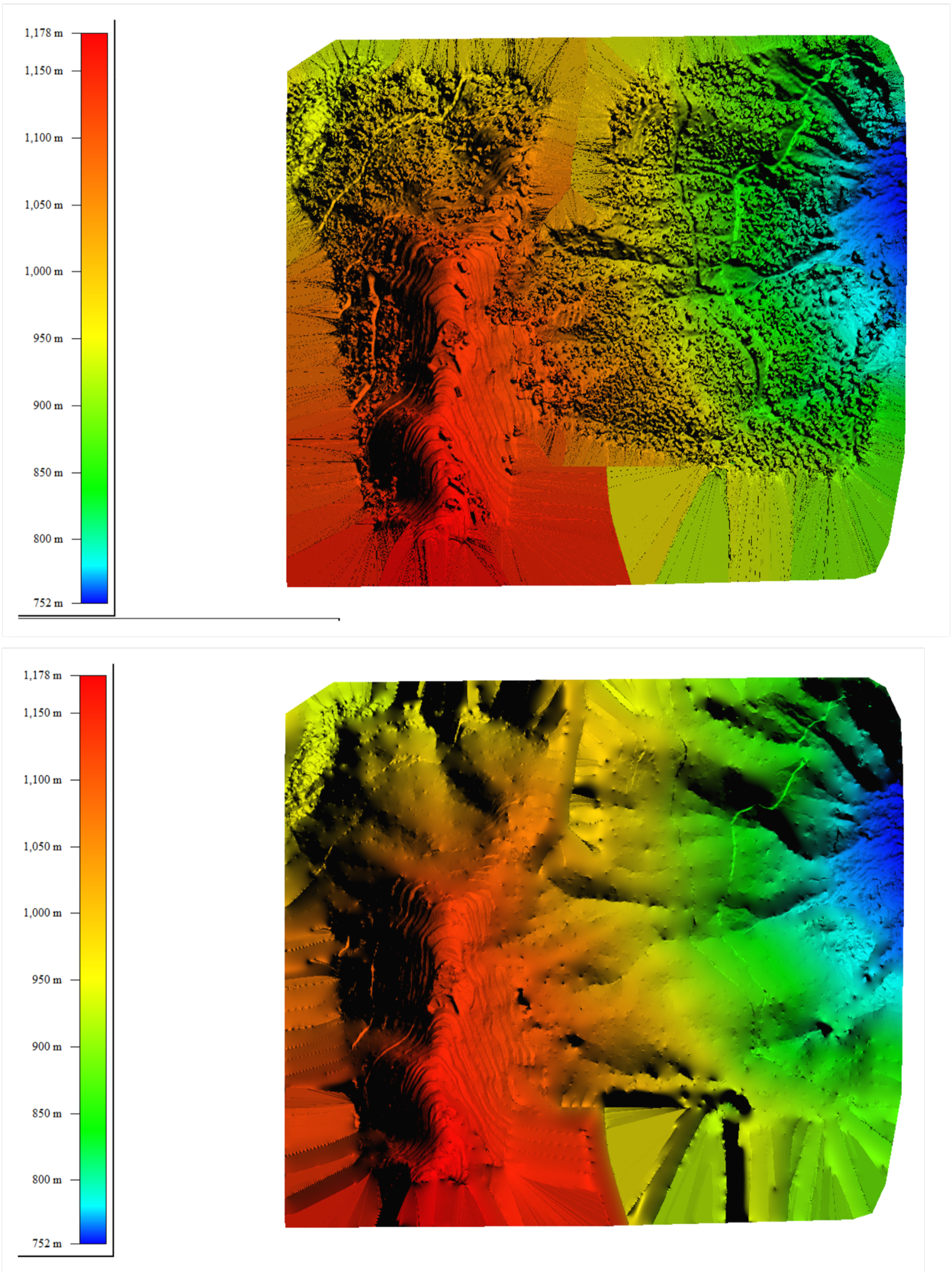

Figure 8 DSM generate from point cloud (top) and DTM generated after processing of DSM (bottom) of cluster 32-74

2.7. Generation of Canopy Height Model (CHM)

2.7.1. Canopy Height Model

Canopy height model (CHM) contains important information about the tree height and is the basic indicator regarding the forest structure (Mojdeh Miraki, Sohrabi, Fatehi, & Kneubuehler, 2021). It can be obtained by deducting Digital terrain model (DTM) from Digital surface model (DSM) (M Miraki & Sohrabi, 2022; Mojdeh Miraki et al., 2021; Panagiotidis, Abdollahnejad, Surový, & Chiteculo, 2017). The CHM were processed using 3*3 gausian filter to prevent formation of multiple local maxima (Mojdeh Miraki et al., 2021

$$CHM = DSM - DTM$$

where,

CHM= Canopy height model

DSM= Digital surface model

DTM= Digital terrain model

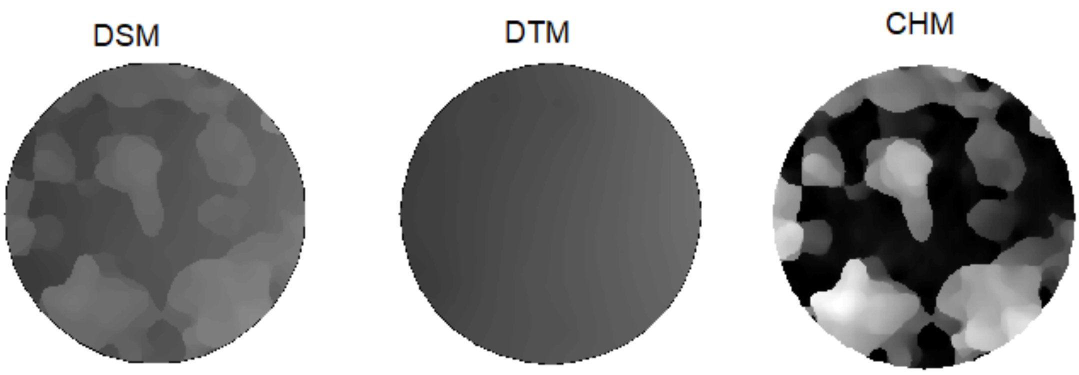

Figure 9 DSM, DTM, CHM

2.7.2. Individual Tree Crown Detection and Delineation

Individual tree crown was detected using multi-resolution segmentation and watershed transformation algorithms. The multi-resolution Segmentation algorithm minimizes the average heterogeneity and maximizes their respective homogeneity (eCognition Developer, 2011). CHM band was weighted thrice the multispectral bands. Watershed transformation algorithm calculates an inverted distance map based on the inverted distances for each pixel to the image object border. Afterwards, the minima are flooded by increasing the level (inverted distance). In areas where the individual catchment basins touch each other (watersheds), the image objects are splited (eCognition Developer, 2011).

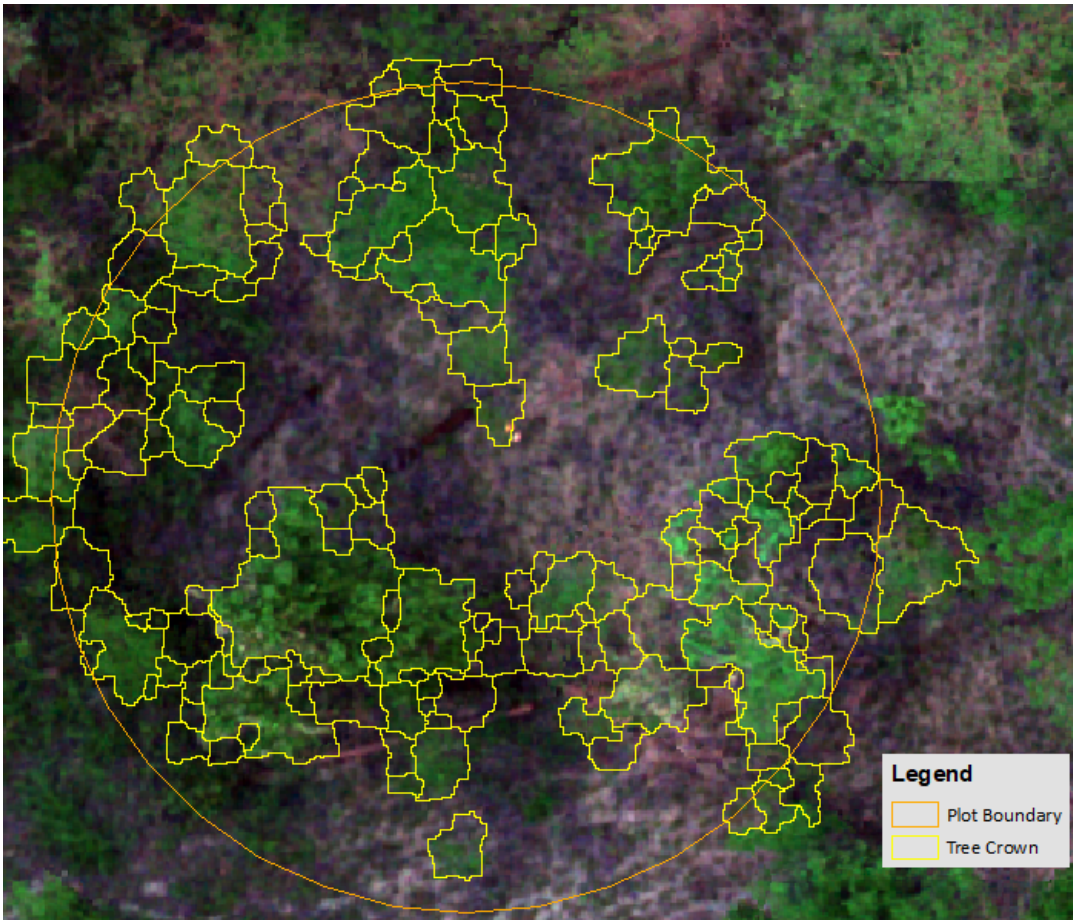

Figure 10 Individual tree tops and crown delineation

2.7.3. Regression Model

Regression is a statistical technique to describe the nature of relationship between variables, and used to forecast/predict variables based on other predictor variables (Ng, Chew, Chng, & Ng, 2018). Coefficient of determination (r2) is a goodness-of-fit measure for linear regression models. This statistic indicates the percentage of the variance in the dependent variable that the independent variables explain collectively. Generally, R-squared measures the strength of the relationship between your model and the dependent variable on a convenient 0 – 100% scale. However, small R-squared values are not always a problem, and high R-squared values are not necessarily good (Jim, 2022)

A hypothesis testing in the regression analysis was also conducted to verify if there is a useful relationship between the dependent variable and the independent variable. The null hypothesis refers to no useful relationship between the dependent variable and the independent variable. If null hypothesis is rejected, the independent variable is considered to be useful in the regression model (Ng et al., 2018).Therefore, to test the significance of the regression, F statistics and T statistics were studied using null and alternate hypothesis. F statistics indicates the overall significance of the regression (whether or not the independent variable contribute significantly to the prediction of dependent variable), while T statistics verifies the significance of the coefficient (Eastman, 1999)

Hypothesis 1:

Ho: There is no significant relation between height derived from UAV (CHM) and height measured from field

HA: There is significant relation between height derived from UAV (CHM) and height measured from field

Hypothesis 2

Ho: There is no significant relation between canopy projection area derived from UAV (CPA) and height measured from field

HA: There is significant relation between canopy projection area derived from UAV (CPA) and height measured from field

Hypothesis 3

Ho: There is no significant relation between canopy height model (CHM) and canopy projection area (CPA)

HA: There is significant relation between canopy height model (CHM) and canopy projection area (CPA)

Hypothesis 4

Ho: There is no significant relation between above ground biomass (AGB) and canopy height model (CHM) and canopy projection area (CPA)

HA: There is significant relation between above ground biomass (AGB) and canopy height model (CHM) and canopy projection area (CPA)

3. RESULTS

3.1. Descriptive Statistics of Field Data

3.1.1. Species Occurrence

A total of 1,262 trees (68 species) were recorded in 66 plots (22 clusters), out of which, *Shorea robusta (25.04%), Pinus roxbhurghii (9.83%), Rhododenron arboretum (6.58%), Pinus wallichiana* (5.39%), *Bauhinia* vahlii (4.99%), *Quercus glauca (4.83%), Terminalia alata (4.75%), Lyonia ovalifolia (4.47%), Tsuga dumosa (3.57%), Quercus semecarpifolia (3.33%)* were the dominant species. The details are presented in following table.

Table 3 Dominant species and their count and percentage

SN	Scientific name	Number	Percentage
1	*Shorea robusta*	316	25.04
2	*Pinus roxburghii*	124	9.83
3	*Rhododendron arboreum*	83	6.58
4	*Pinus wallichinana*	68	5.39
5	*Bauhinia vahlii*	63	4.99
6	*Quercus glauca*	61	4.83
7	*Terminalia alata*	60	4.75
8	*Lyonia ovalifolia*	56	4.44
9	*Tsuga dumosa*	45	3.57
10	*Quercus semecarpifolia*	42	3.33
	Other Species	344	27.26

3.1.2. Diameter at breast height

Around 49 trees had 5-10 cm diameter, 95 trees had 10-20 cm diameter, 169 trees had 20-50 cm diameter and 28 trees had diameter of more than 50 cm. *Shorea robusta* had the highest number of trees with diameter of 10-20 cm and 20-50 cm, while *Terminalia alata* had the highest number of trees with diameter above 50 cm. The details are presented in following table.

Table 4 DBH class according to species

SN	Scientific names	Diameter (cm)					
		<5	5_10	10_20	20-50	>50	total
1	*Shorea robusta*	5	19	117	156	19	316
2	*Pinus roxburghii*	0	9	36	73	6	124
3	*Rhododendron arboreum*	0	4	13	52	14	83
4	*Pinus wallichinana*	0	0	17	50	1	68
5	*Bauhinia vahlii*	0	41	20	2	0	63
6	*Quercus glauca*	0	0	9	52	0	61
7	*Terminalia alata*	0	2	11	23	24	60
8	*Lyonia ovalifolia*	0	16	24	15	1	56
9	*Tsuga dumosa*	0	10	14	11	10	45
10	*Quercus semecarpifolia*	0	1	7	33	1	42
	Other Species	3	49	95	169	28	344

The diameter ranged from 5 to 98 cm. *Terminalia alata* had the highest mean diameter of 43.9 cm , followed by *Rhododendron arboretum* (34.6 cm). *Terminalia alata* and *Tsuga dumosa* had the largest diameter of 98.3 cm followed by *Rhododendron arboretum* of 96.5 cm while, *Bauhinia vahlii* and *Lyonia ovalifolia* had the smallest diameter of 5 cm. Majority of the diameter values were positively skewed and symmetrically distributed whereas, there were presence of high degree of outliers in the distribution of *Quercus semecarpifolia* species. The details are presented in following table.

Table 5 Summary of diameter (cm) of dominant species

Species	N	Mean	Median	Min	Max	Range	Std. Dev	Variance	Kurtosis	Skewness
Shorea robusta	311	24.3	21.2	5.4	80.2	74.8	13.3	178.0	1.9	1.3
Pinus roxburghii	124	24.3	21.6	5.4	74.3	68.9	12.8	164.4	2.2	1.3
Rhododendron arboreum	83	34.6	33.1	5.1	96.5	91.4	18.2	331.3	0.8	0.8
Pinus wallichiana	68	28.3	26.6	10.2	57	46.8	10.8	117.5	-0.5	0.4
Bauhinia vahlii	63	9.9	8.7	5	24	19	4.2	17.8	1.6	1.4
Quercus glauca	61	29.4	30.1	11.3	42.9	31.6	8.6	73.3	-0.6	-0.5
Terminalia alata	60	43.9	42.3	7.5	98.3	90.8	22.8	521.2	-0.5	0.4
Lyonia ovalifolia	56	16.9	12.6	5	53.7	48.7	11.6	133.6	1.9	1.5
Tsuga dumosa	45	29.8	16	5.2	98.3	93.1	25.0	625.6	0.1	1.0
Quercus semecarpifolia	42	29.3	28.35	8.9	78.5	69.6	12.0	143.4	5.8	1.6

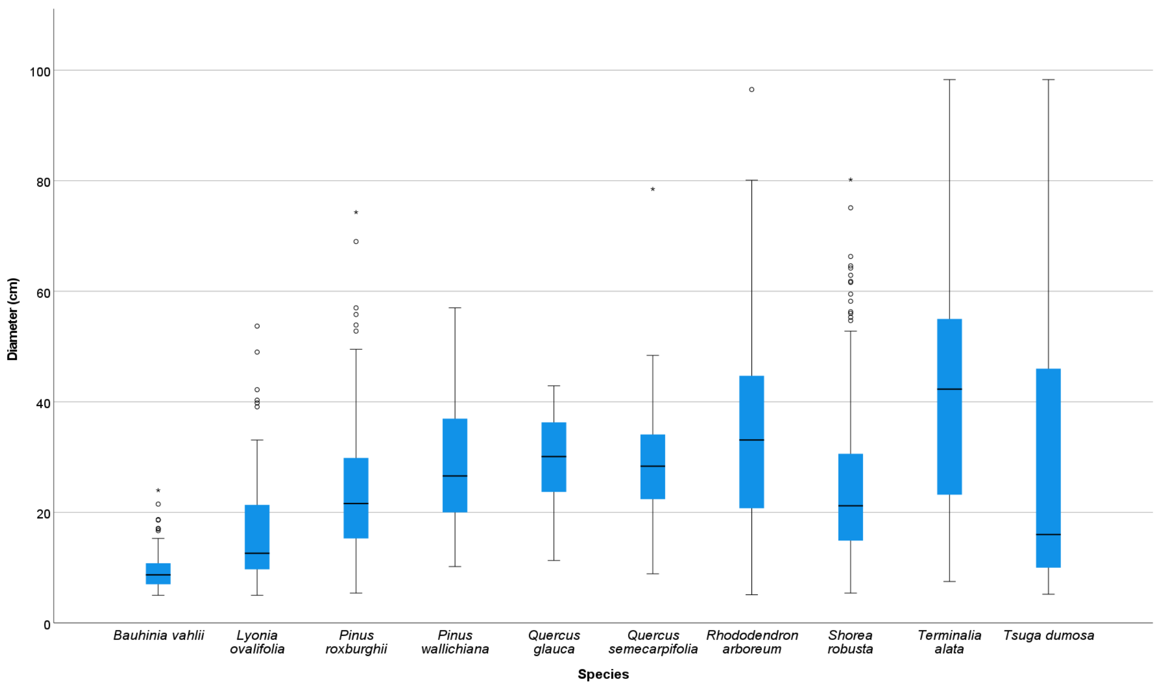

Figure 11 Diameter (cm) of dominant species

3.1.3. Height

The height ranged from 0.6 to 37.6 m. *Terminalia alata* had the highest mean height of 19.3m and *Tsuga dumosa* had the maximum height of 38.2m. The height was found to be symmetrically distributed with few outliers in *Shorea robusta* and *Tsuga dumosa* species. The details are presented in the following table.

Species	N	Mean	Median	Min	Max	Range	Std. Dev	Variance	Kurtosis	Skewness
Shorea robusta	133	13.6	13.1	1.6	35	33.4	5.7	33.0	1.3	0.9
Bauhinia vahlii	63	14.2	15	2	25	23	7.9	62.6	-1.5	-0.1
Pinus roxburghii	59	15.7	17.1	3.7	28.9	25.2	6.5	42.0	-1.0	-0.2
Terminalia alata	28	19.3	18.9	2.9	35.7	32.8	9.0	81.8	-0.8	0.1
Rhododendron arboreum	22	8.7	8.95	1.8	14.3	12.5	3.6	12.9	-0.8	-0.3
Lyonia ovalifolia	20	6.2	5.8	0.6	10.8	10.2	3.0	9.2	-1.1	0.0
Pinus wallichiana	18	15.9	18.2	1.2	25	23.8	7.3	53.6	-0.2	-0.9
Quercus glauca	16	14.6	14.7	6	21.3	15.3	5.0	25.5	-1.1	-0.4
Tsuga dumosa	15	10.2	5.3	0.6	38.2	37.6	11.7	136.0	0.8	1.4
Quercus semecarpifolia	9	12.5	13.9	5	19	14	4.6	21.3	-0.6	-0.5

. Height (m) of dominant species

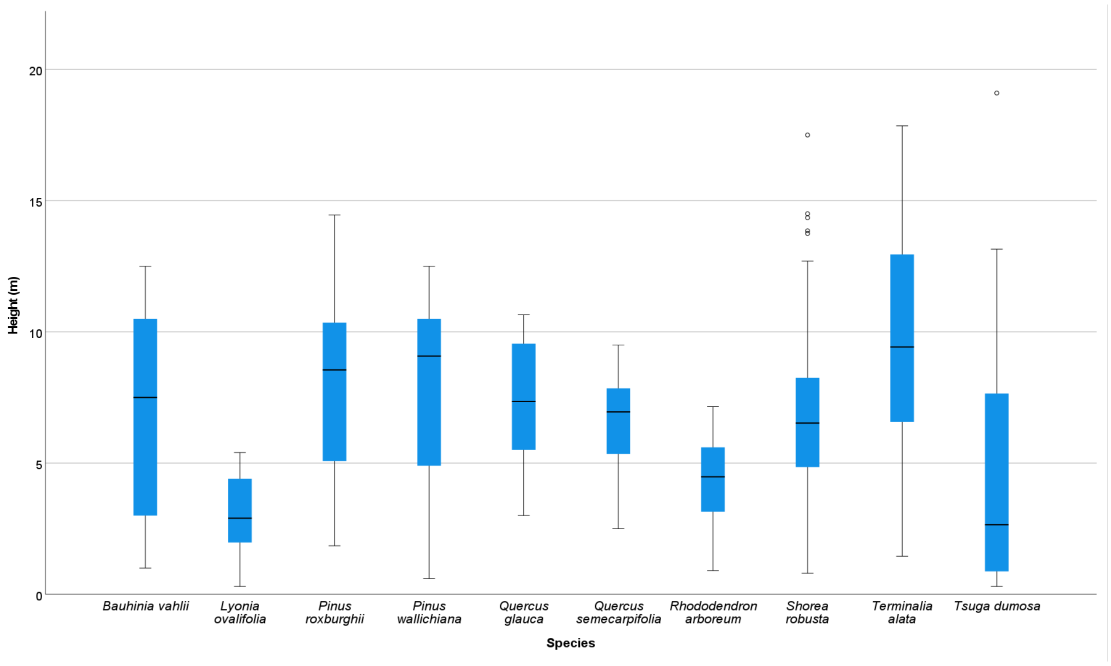

Figure 12 Height (m) of dominant species

3.1.4. Volume

The total volume ranged from 0.003 to 12.4 m^3. *Shorea robusta* had the largest volume (79.4 m^3), followed by *Terminalia alata* (48.1 m^3), while *Lyonia ovalifolia* had the least volume (3.2 m^3). Majority of the species' volume distribution was found to be positively skewed and presence of outliers. **Error! Reference source not found.** represents further details of other species.

Table 6 Total volume (m^3) of dominant species

Species	N	Mean	Median	Sum	Min	Max	Range	Std. Dev	Variance	Kurtosis	Skewness
Shorea robusta	133	0.6	0.3	79.4	0.006	4.9	4.9	0.9	0.8	6.4	2.5
Bauhinia vahlii	63	0.1	0.0	4.3	0.004	0.3	0.3	0.1	0.0	2.4	1.8
Pinus roxburghii	59	0.6	0.4	33.5	0.012	5.9	5.9	0.9	0.8	20.1	4.1
Terminalia alata	28	1.7	1.1	48.1	0.017	8.2	8.2	2.1	4.4	2.7	1.7
Rhododendron arboreum	22	0.5	0.2	10.0	0.004	1.6	1.6	0.5	0.2	0.7	1.2
Lyonia ovalifolia	20	0.2	0.1	3.2	0.003	1.1	1.1	0.3	0.1	9.0	2.9
Pinus wallichiana	18	0.7	0.5	12.5	0.023	2.7	2.7	0.7	0.5	2.9	1.5
Quercus glauca	16	0.6	0.5	9.2	0.046	1.3	1.2	0.4	0.2	-0.7	0.5
Tsuga dumosa	15	1.5	0.1	22.2	0.008	12.4	12.3	3.3	10.7	9.8	3.0
Quercus semecarpifolia	9	0.5	0.6	4.9	0.047	1.0	1.0	0.3	0.1	0.1	-0.2

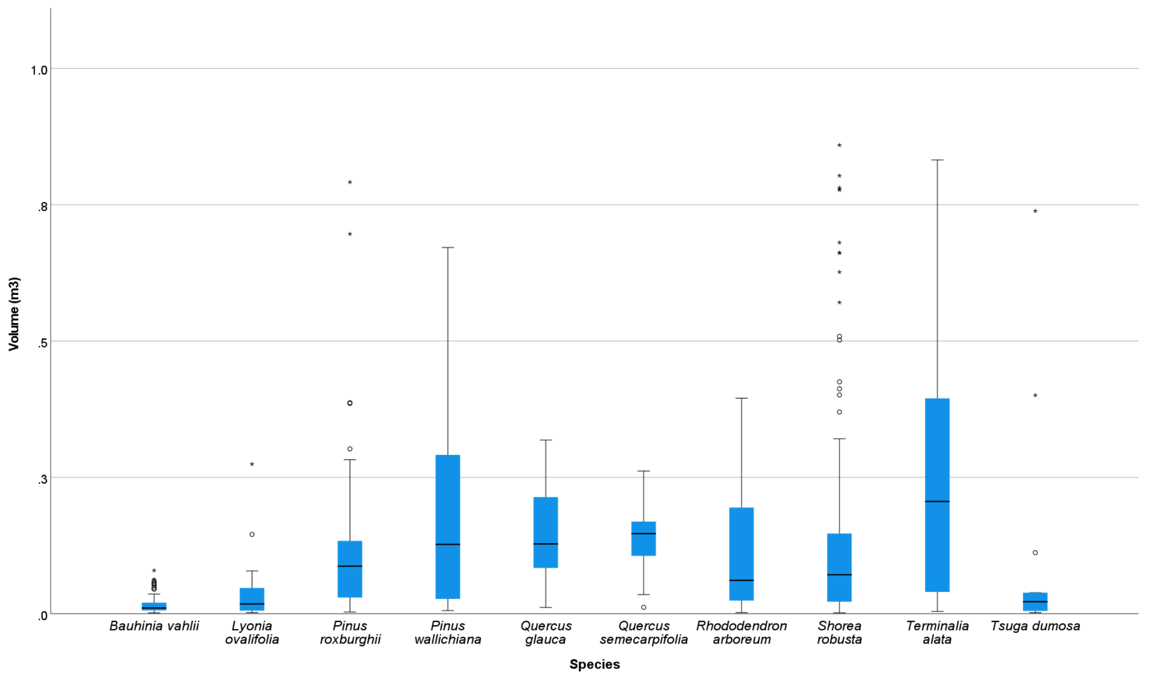

Figure 13 Volume (m^3) of dominant species

3.1.5. Above Ground Biomass

Shorea robusta had the highest above ground biomass (AGB) of about 96188.2 kg, followed by *Pinus roxbhurghii* (28,494.40 kg) . Majority of the distribution of species' biomass was found to be positively skewed with presence of high degree of outliers. Other details are presented in Table 7.

Table 7 Total biomass (kg) of the dominant species

Species	N	Mean	Median	Sum	Min	Max	Range	Std. Dev	Variance	Kurtosis	Skewness
Shorea robusta	133	723.2	286.6	96188.2	5.5	6238.7	6233.2	1108.8	1229497.0	6.4	2.5
Bauhinia vahlii	63	68.0	40.8	4286.2	4.0	314.5	310.4	70.6	4988.1	2.4	1.8
Pinus roxburghii	59	483.0	300.8	28494.4	10.1	5086.2	5076.0	795.1	632188.1	20.3	4.1
Terminalia alata	28	2357.8	1512.9	66019.1	24.0	11274.3	11250.3	2872.2	8249657.9	2.7	1.7
Rhododendron arboreum	22	615.5	249.1	13541.1	3.9	2322.9	2319.0	709.8	503797.8	1.1	1.4
Lyonia ovalifolia	20	198.3	82.4	3966.8	3.4	1264.9	1261.5	305.4	93275.3	7.8	2.6
Pinus wallichiana	18	448.8	338.0	8078.7	16.0	1558.3	1542.3	410.7	168640.2	1.8	1.3
Quercus glauca	16	761.6	660.3	12184.9	55.9	1725.8	1670.0	535.7	287006.1	-0.7	0.5
Tsuga dumosa	15	935.2	70.2	14028.7	5.0	7781.4	7776.4	2055.9	4226735.5	9.8	3.0
Quercus semecarpifolia	9	996.1	1061.1	8964.7	79.5	1962.1	1882.6	578.3	334425.8	0.1	-0.2

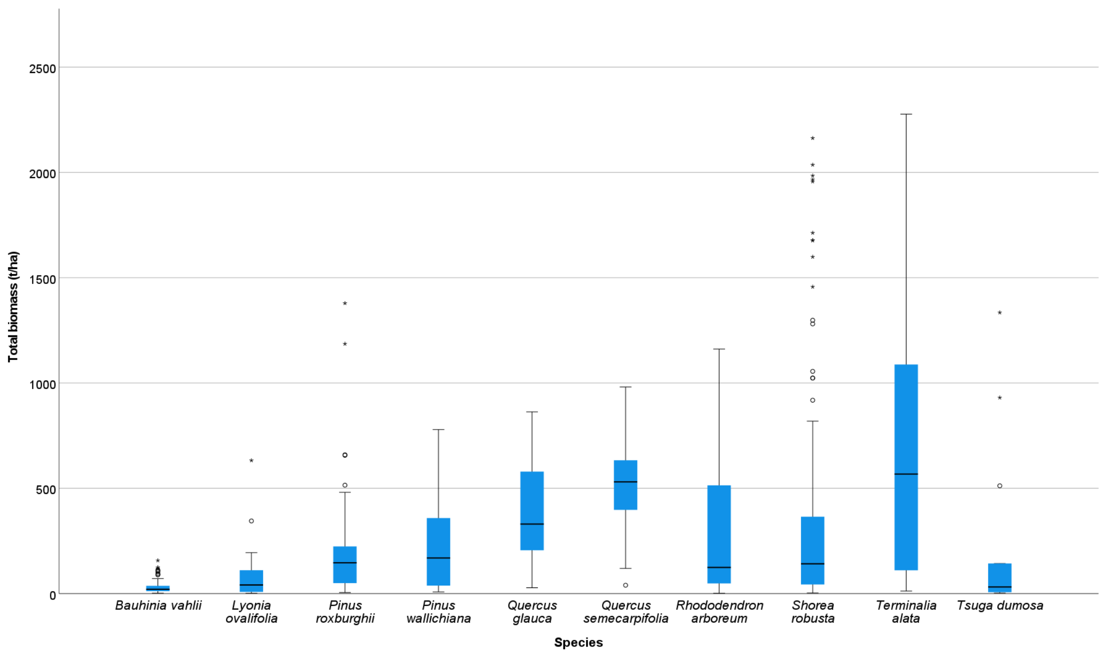

Figure 14 Total biomass (kg) of the dominant species

3.2. Regression Analysis

3.2.1. Relation between CHM and Tree Height from Field

Overall Tree Species

Regression analysis showed that CHM and field height had higher coefficient of determination (r^2) of 0.78 for overall tree species in the sampled plots.

The results of F and T statistics rejects the null hypothesis of hypothesis 1 that states there is no significant relation between height derived from UAV (CHM) and height measured from field at 95% confidence level. This concludes there is significant relation between CHM and field height.

The summary of regression model, F statistics and T statistics are presented in following table and details are provided in Annex.

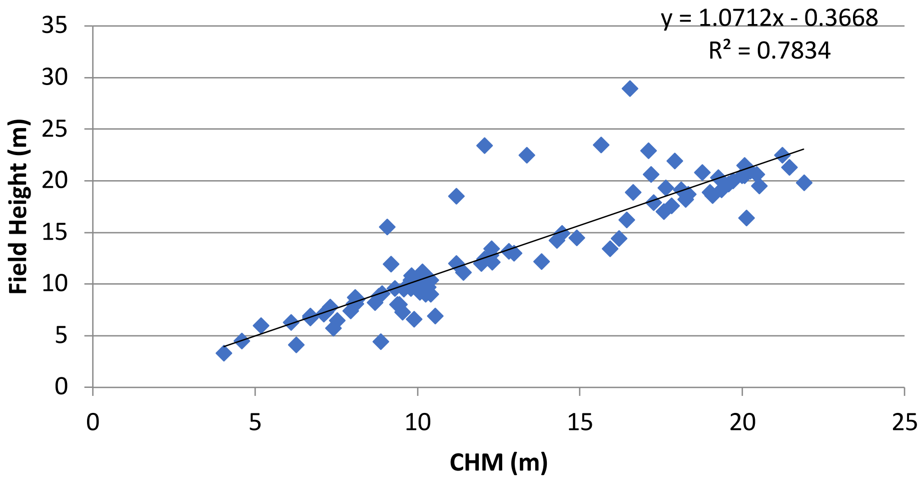

Figure 15 Regression model (CHM and Field Height) for overall tree species

Individual Tree Species

Except for *Pinus roxbhurghii,* coefficient of determination (r^2) was higher (above 0.6) for *Shorea robusta, Buchanania latifolia and Terminalia alata*.

T and F statistics showed that the relation between CHM and field height was significant for *Shorea robusta, Pinus roxbhurghii, Buchanania latifolia and Terminalia alata*. This rejects the null hypothesis of hypothesis 1 that states there is no significant relation between height derived from UAV (CHM) and height measured from field at 95% confidence level.

The summary of regression model, F statistics and T statistics are presented in following table and details are provided in Annex.

Table 8 Summary of regression model, F statistics, T statistics and P value for CHM and field height

Species	r^2	Regression model	F statistics	T statistics	P value
Overall tree species	0.78	y = 1.0712x - 0.3668	332.8367	18.24381	2.55E-32
Shorea robusta	0.872	y = 0.9485x + 0.2182	279.3554	16.71393	6.57E-20
Pinus roxbhurghii	0.37	y = 0.7808x + 5.5	14.23843	3.773384	0.000932

Buchanania latifolia	0.66	y = 0.7147x + 1.1571	9.830931	3.135432	0.025799
Terminalia alata	0.66	y = 0.3354x + 13.561	9.724746	3.118452	0.026298

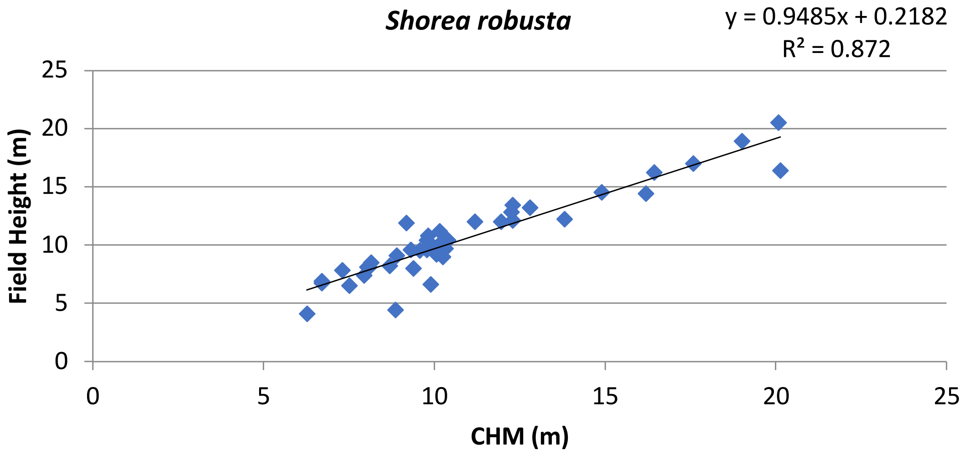

Figure 16 Regression model (CHM and Field Height) for Shorea robusta

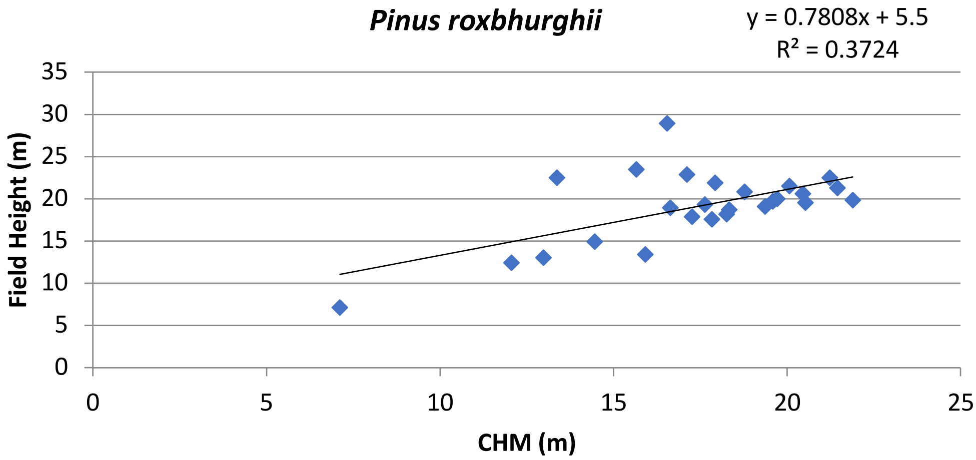

Figure 17 Regression model (CHM and Field Height) for overall Pinus roxbhurghii

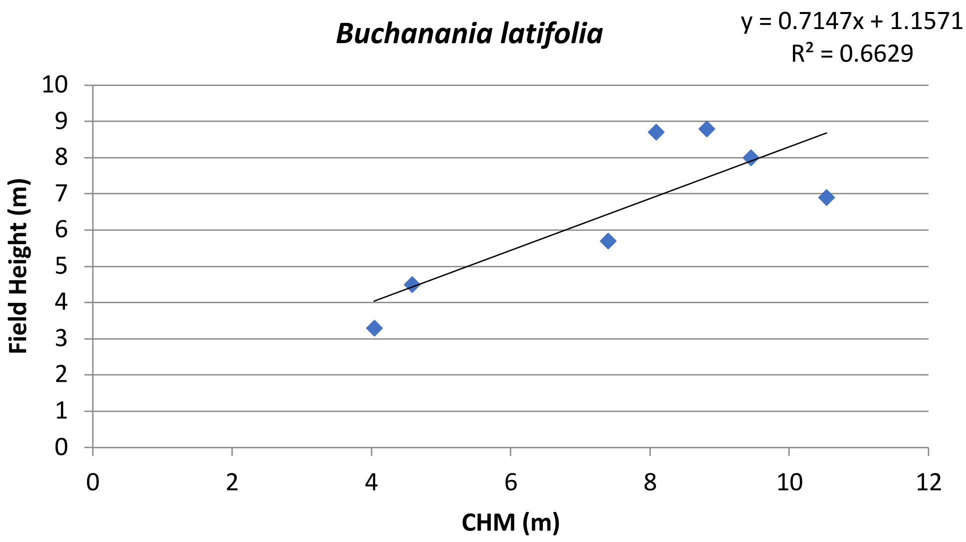

Figure 18 Regression model (CHM and Field Height) for Buchanania latifolia

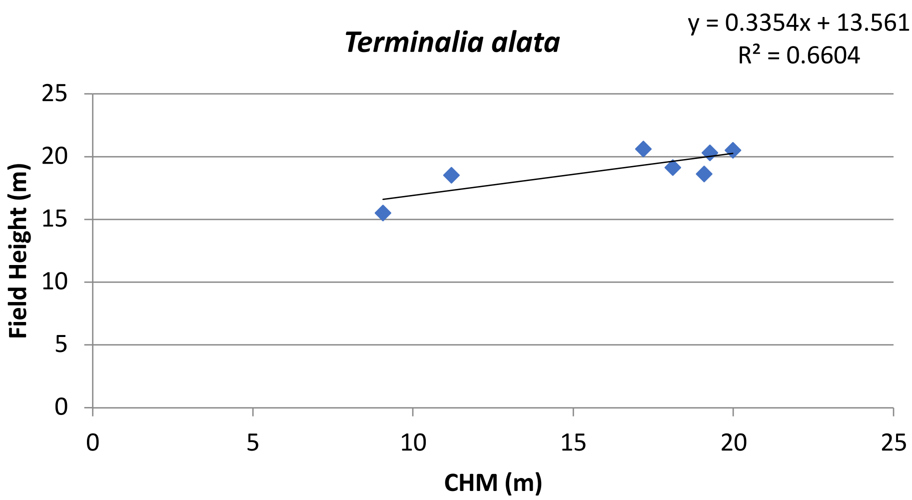

Figure 19 Regression model (CHM and Field Height) for Terminalia alata

3.2.2. Relation between Crown Projection Area (CPA) and Tree Inventory Height

Overall Tree Species

Regression analysis showed that UAS generated CPA and tree height from field inventory had coefficient of determination (r^2) of 0.78 for overall tree species in the sampled plots.

T and F statistics showed that the relation between CPA and field height was significant, which rejects the null hypothesis of hypothesis 2 that states there is no significant relation between canopy projection area derived from UAV (CPA) and height measured from field at confidence interval of 95%.

The summary of regression model, F statistics and T statistics are presented in following table and details are provided in Annex.

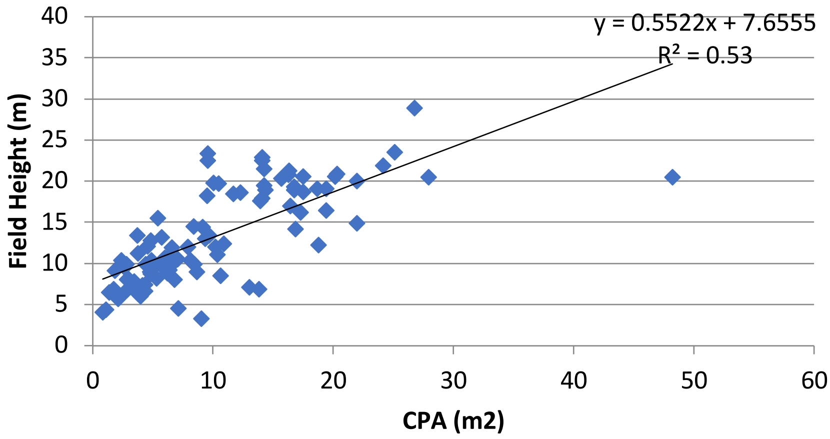

Figure 20 Regression model (CPA and Field Height) for overall tree species

Individual Tree Species

The coefficient of determination (r^2) was above 0.5 for *Shorea robusta, and Terminalia alata, while Pinus roxbhurghii and Buchanania latifolia had r^2 of 0.25 and 0.02 respectively.*

T and F statistics showed that the relation between CPA and field height was significant for *Shorea robusta, Pinus roxbhurghii and and Terminalia alata*. This rejects the null hypothesis of hypothesis 2 that states there is no significant relation between canopy projection area derived from UAV (CPA) and height measured from field at 95% confidence level.

In the case of *Buchanania latifolia, the null hypothesis was accepted and the* relation between CPA and field height was not found significant

The summary of regression model, F statistics and T statistics are presented in following table and details are provided in Annex.

Table 9 Summary of regression model, F statistics, T statistics and P value for CPA and Field Height

Species	r^2	Regression model	F statistics	T statistics	P value
Overall tree species	0.53	y = 0.5522x + 7.6555	103.7538	10.18596	9.3E-17
Shorea robusta	0.58	y = 0.3446x + 8.075	57.69058	7.595432	2.41E-09
Pinus roxbhurghii	0.2544	y = 0.3912x + 12.995	8.186847	2.861267	0.008608
Buchanania latifolia	0.0227	y = -0.0882x + 7.1852	0.115979	-0.34056	0.74728
Terminalia alata	0.655	y = 0.2063x + 15.8	9.493671	3.08118	0.027433

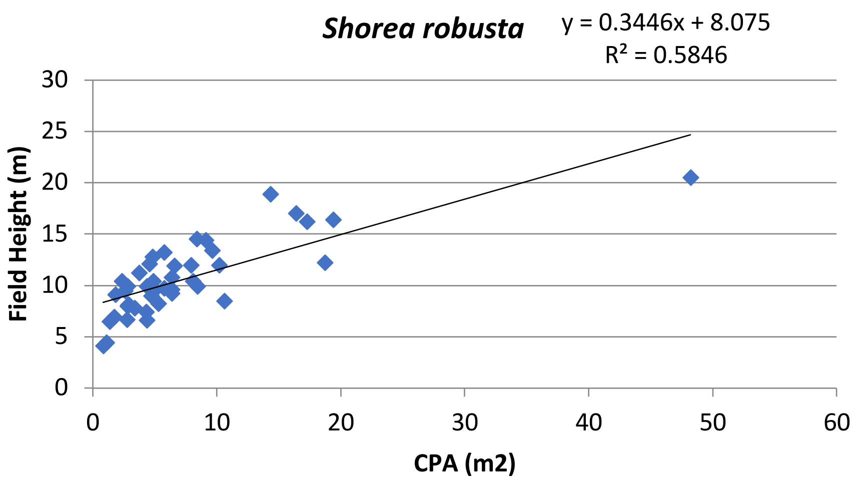

Figure 21 Regression model (CPA and Field Height) for Shorea robusta

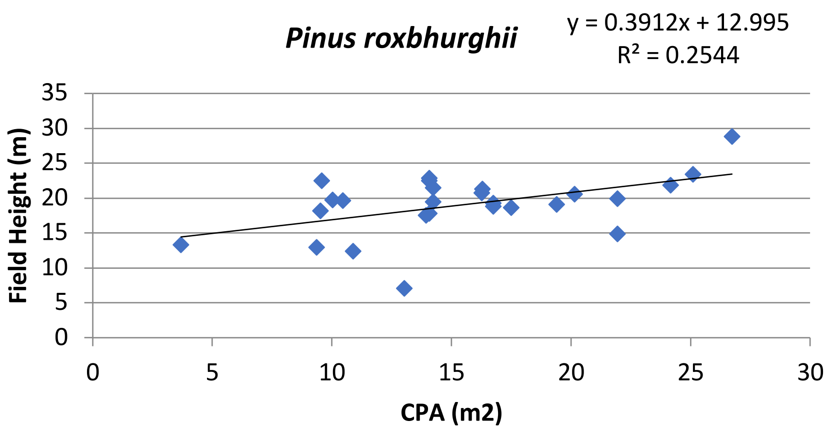

Figure 22 Regression model (CPA and Field Height) for Pinus roxbhurghii

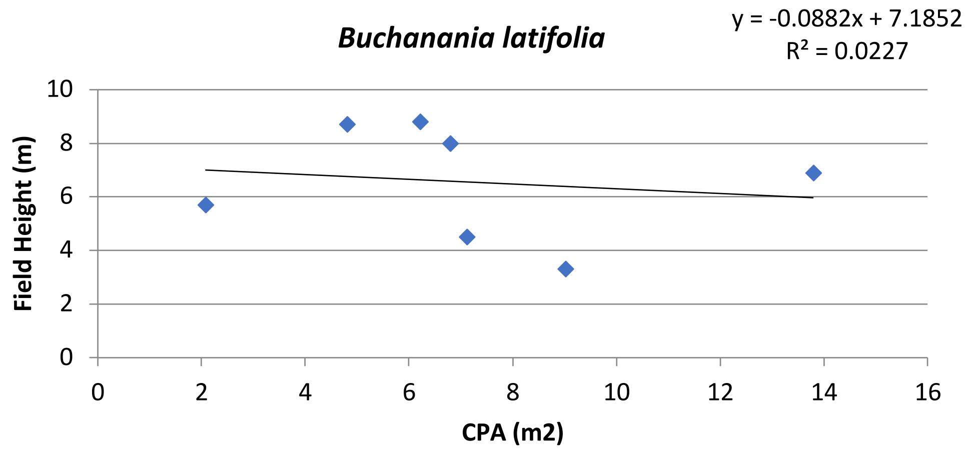

Figure 23 Regression model (CPA and Field Height) for Buchanania latifolia

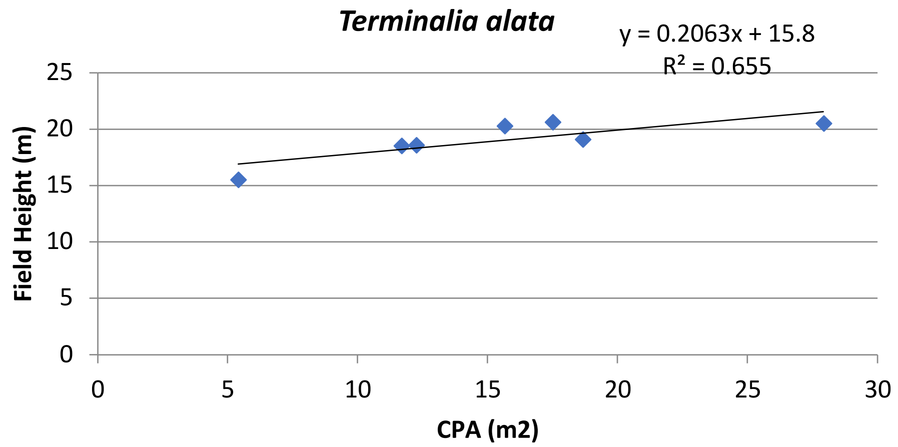

Figure 24 Regression model (CPA and Field Height) for Terminalia alata

3.2.3. *Relation between CHM and CPA*

Overall Tree Species

Regression analysis showed that coefficient of determination (r^2) was 0.52 for overall tree species in the sampled plots.

T and F statistics showed that the relation between CHM and CPA was significant, which rejects the null hypothesis of hypothesis 3 that states there is no significant relation between CHM and CPA at confidence interval of 95%.

The summary of regression model, F statistics and T statistics are presented in following table and details are provided in Annex.

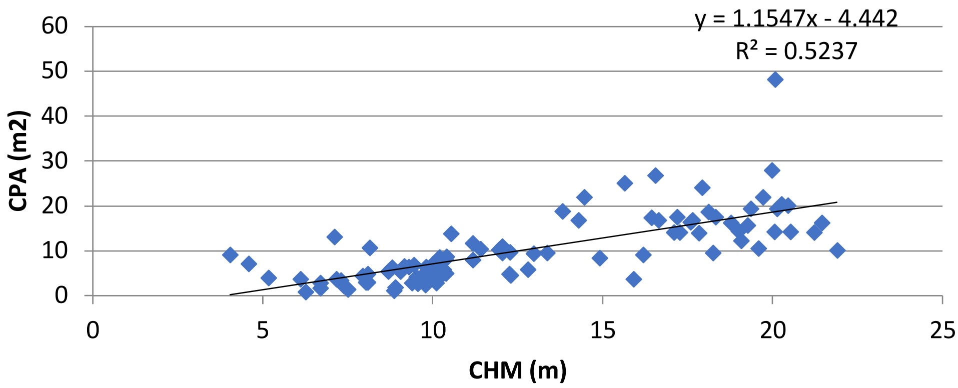

Figure 25 Regression model (CHM and CPA) for overall tree species

Individual Tree Species

The coefficient of determination (r^2) was above 0.5 for *Shorea robusta, and Terminalia alata, while Pinus roxbhurghii and Buchanania latifolia had r^2 of 0.02 and 0.04 respectively.*

T and F statistics showed that the relation between CHM and CPA was significant for *Shorea robusta, and Terminalia alata, which* rejects the null hypothesis of hypothesis 3 that states there is no significant relation between CHM and CPA at 95% confidence level.

In the case of*, Pinus roxbhurghii, Buchanania latifolia* the null hypothesis was accepted, which concludes an insignificant relation between CHM and CPA.

The summary of regression model, F statistics and T statistics are presented in following table and details are provided in Annex.

Table 10 Summary of regression model, F statistics, T statistics and P value for CHM and CPA

Species	r^2	Regression model	F statistics	T statistics	P value
Overall tree species	0.5237	y = 1.1547x - 4.442	101.1744893	10.05855304	1.72088E-16
Shorea robusta	0.5968	y = 1.7408x - 11.688	60.69108	7.790448	1.29E-09
Pinus roxbhurghii	0.0206	y = 0.2369x + 11.419	0.505587	0.711046	0.483909
Buchanania latifolia	0.0426	y = 0.3092x + 4.7819	0.222484	0.471682	0.657019
Terminalia alata	0.5674	y = 1.2193x - 4.2506	6.557824	2.560825	0.050596

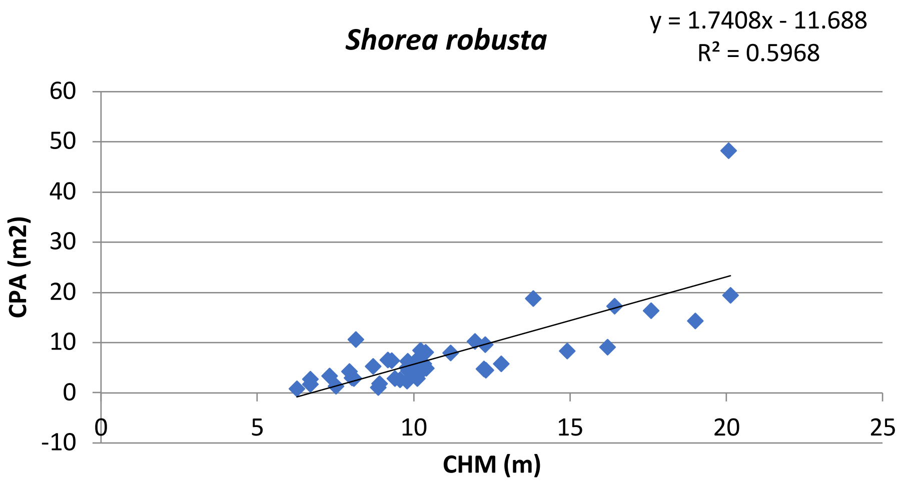

Figure 26 Regression model (CHM and CPA) for Shorea robusta

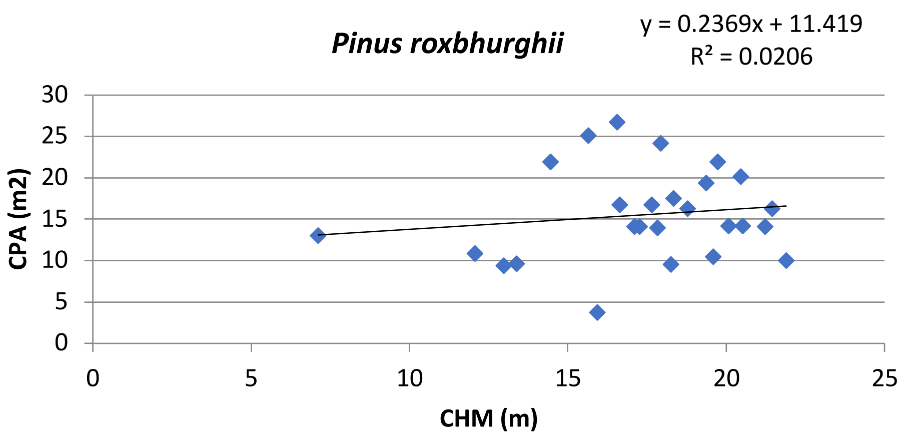

Figure 27 Regression model (CHM and CPA) for Pinus roxbhurghii

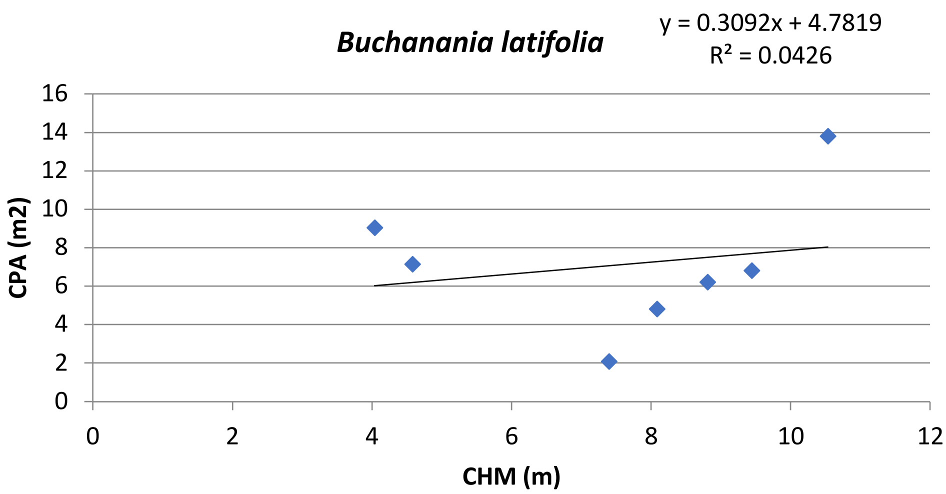

Figure 28 Regression model (CHM and CPA) for Buchanania latifolia

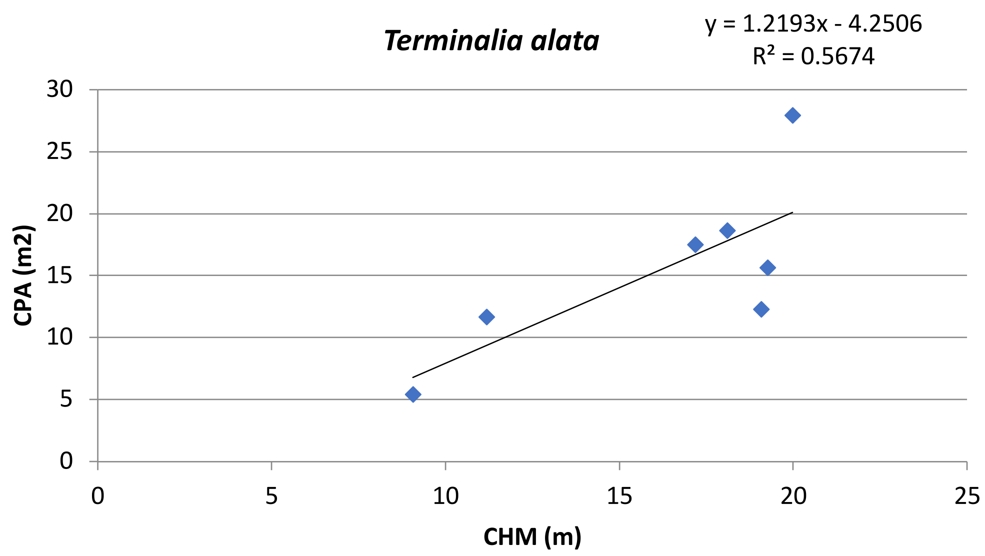

Figure 29 Regression model (CHM and CPA) for Terminalia alata

3.2.4. Relation between Above Ground Biomass and CPA and CHM

Overall Tree Species

Regression analysis between AGB, CPA and CHM showed that coefficient of determination (r^2) was 0.36 for overall tree species in the sampled plots.

F statistics showed that the relation between AGB, CHM and CPA was significant, which rejects the null hypothesis of hypothesis 4 that states there is no significant relation between AGB, CHM and CPA at confidence interval of 95%. However, T statistics showed that CPA had significant relation with AGB and CHM did not have significant relation with AGB

The summary of regression model, F statistics and T statistics are presented in following table and details are provided in Annex.

Individual Tree Species

The coefficient of determination (r^2) was above 0.5 for *Shorea robusta only. Pinus roxbhurghii, Buchanania latifolia and Terminalia alata,* had r^2 of 0.16, 0.37 and 0.12respectively.

T and F statistics showed that the relation between AGB, CHM and CPA was significant for *Shorea robusta,* only*,* which rejects the null hypothesis of hypothesis 4 that states there is no significant relation between AGB, CHM and CPA at confidence interval of 95%.

In the case of *Pinus roxbhurghii, Buchanania latifolia and Terminalia alata,* the null hypothesis was accepted, which concludes an insignificant relation between AGB, CHM and CPA.

The summary of regression model, F statistics and T statistics are presented in following table and details are provided in Annex.

Table 11 Summary of regression model, F statistics, T statistics and P value for AGB, CHM and CPA

Species	r2	Regression model	F statistics	F Significance	CHM (T-statistics)	CHM (P value)	CPA (T-statistics)	CPA (P value)
Overall tree species	0.367986	AGB = 71.67 CPA - 7.53 CHM – 175.64	26.49211	8.57147E-10	-0.34703	0.729367	5.268775	9.15E-07
Shorea robusta	0.890648	AGB = 67.95 CPA + 39.05 CHM – 558.4	162.8963	5.98E-20	2.41992	0.02016	9.488009	8.6E-12
Pinus roxbhurghii	0.167494	AGB = 71.13 CPA -12.43 CHM – 404.68	2.313714	0.121466	-0.22769	0.821899	2.149585	0.042341
Buchanania latifolia	0.378004	AGB = 28.45CHM-13.13 CPA – 6.05	1.215454	0.386879	1.396717	0.235011	-0.96625	0.388637
Terminalia alata	0.127474	AGB=69.74 CPA -4.28 CHM+832.44	0.292196	0.761301	-0.01965	0.985267	0.517437	0.632149

4. CONCLUSIONS

Regression analysis between canopy height model (CHM) generated from UAV and field height showed higher r2 (0.7) for overall tree species. *Pinus roxbhurghii* had lower r^2 (0.37) compared to *Shorea robusta, Buchanania latifolia and Terminalia alata* (above 0.6). T and F statistics also showed significant relation between CHM and field height for all species at 95% confidence level.

Regression analysis between CPA and tree height showed higher r^2 (0.78) for overall tree species. *Shorea robusta and Terminalia alata* had higher r^2 (above 0.5) compared to *Pinus roxbhurghii and Buchanania latifolia* (below 0.2). T and F statistics showed significant relation between CPA and field height for *Shorea robusta, Pinus roxbhurghii and and Terminalia alata* at 95% confidence level.

Regression analysis between CHM and CPA showed higher r^2 (0.52) for overall tree species. *Shorea robusta, and Terminalia alatan* had higher r2 (above 0.5) compared *Pinus roxbhurghii and Buchanania latifolia* (less than 0.04). T and F statistics showed significant relation between CHM and CPA for *Shorea robusta, and Terminalia alata* only at 95% confidence level.

Regression analysis between AGB, CPA and CHM showed r^2 of 0.36 for overall tree species. *Shorea robusta* had higher r^2 (above 0.5), while *Pinus roxbhurghii, Buchanania latifolia and Terminalia alata,* had low r^2. T and F statistics showed significant relation between AGB, CHM and CPA for *Shorea robusta* only at confidence interval of 95%.

5. RECOMMENDATIONS FOR SIMILAR STUDY

Following recommendations are made based on the learning and experience of this study:

- For undertaking UAS based forest inventory in steep terrain of hilly and mountainous regions, UAS operating in “visual line-of-sight (VLOS)” is deemed not very suitable. UAS that operates in “beyond visual line of sight (BVLOS)” with longer operating time is suitable. However, operating such UAS requires special permissions and advance training.
- Base point/control point markers should be established clearly while operating the UAS for higher accuracy. Reliability of RTK, using online based Precise Point Positioning (PPP) may vary depending on the availability and quality of internet connectivity.
- Cross-flight configuration at different heights will capture images from different angle, which will minimize occlusions in certain degree.
- Crown diameter of each tree along with crown overlapping percentage should be noted in the field.
- Photograph of the tree crown should also be taken so that tree crown overlapping pattern can be identified for accuracy assessment.
- Inventory tally trees for sampling (image training) should be located using high precision GNSS system in compliance to the GNSS system used in RTK based UAS.
- UAS survey and trees location measurement should be done from the same GNSS base station in a plot.

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Annex 1: Regression, F Statistics, T Statistics of AGB, CPA and CHM

Overall tree species

Regression Statistics	
Multiple R	0.606619
R Square	0.367986
Adjusted R Square	0.354096
Standard Error	692.563
Observations	94

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	25413542	12706771	26.49211	8.57147E-10
Residual	91	43647565	479643.6		
Total	93	69061107			

T statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-175.64	213.9549	-0.82092	0.413836	-600.63558	249.3549	-600.636	249.3549
CHM (m)	-7.53239	21.70504	-0.34703	0.729367	-50.64678325	35.582	-50.6468	35.582
CPA (m2)	71.67164	13.60309	5.268775	9.15E-07	44.65076196	98.69251	44.65076	98.69251

Shorea robusta

Regression Statistics	
Multiple R	0.943742
R Square	0.890648
Adjusted R Square	0.885181
Standard Error	233.3684
Observations	43

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	17742936	8871468	162.8963	5.98E-20
Residual	40	2178433	54460.82		
Total	42	19921369			

T Statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-558.4	144.7301	-3.85822	0.000407	-850.911	-265.89	-850.911	-265.89
CHM (m)	39.05495	16.13895	2.41992	0.02016	6.43693	71.67298	6.43693	71.67298
CPA (m2)	67.95576	7.162278	9.488009	8.6E-12	53.48026	82.43127	53.48026	82.43127

Pinus roxbhurghii

Regression Statistics	
Multiple R	0.40926
R Square	0.167494
Adjusted R Square	0.095102
Standard Error	904.8832
Observations	26

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	3789001	1894501	2.313714	0.121466
Residual	23	18832714	818813.6		
Total	25	22621715			

T statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-404.681	1027.763	-0.39375	0.697392	-2530.77	1721.408	-2530.77	1721.408
CHM (m)	-12.4302	54.59253	-0.22769	0.821899	-125.363	100.5031	-125.363	100.5031
CPA (m2)	71.13805	33.09385	2.149585	0.042341	2.678213	139.5979	2.678213	139.5979

Annex 1-3

Buchanania latifolia

Regression Statistics	
Multiple R	0.61482
R Square	0.378004
Adjusted R Square	0.067006
Standard Error	118.842
Observations	7

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	34332.75	17166.37	1.215454	0.386879
Residual	4	56493.72	14123.43		
Total	6	90826.47			

T statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-6.05885	170.0689	-0.03563	0.973288	-478.246	466.128	-478.246	466.128
CHM (m)	28.45243	20.37093	1.396717	0.235011	-28.1064	85.01121	-28.1064	85.01121

Annex 1-4

CPA (m2)	-13.1392	13.59813	-0.96625	0.388637	-50.8936	24.6153	-50.8936	24.6153

Terminalia alata

Regression Statistics	
Multiple R	0.753255
R Square	0.567393
Adjusted R Square	0.480871
Standard Error	5.051861
Observations	7

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	167.3642	167.3642	6.557824	0.050596
Residual	5	127.6065	25.5213		
Total	6	294.9707			

T statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-4.25056	7.974675	-0.53301	0.616858	-24.7501	16.24899	-24.7501	16.24899
CHM (m)	1.219345	0.476153	2.560825	0.050596	-0.00465	2.443335	-0.00465	2.443335

Annex 1-5

Annex 2: Regression, F Statistics, T Statistics of CPA and CHM

Overall tree species

Regression Statistics	
Multiple R	0.723703
R Square	0.523747
Adjusted R Square	0.51857
Standard Error	5.307961
Observations	94

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2850.535	2850.535075	101.1744893	1.72E-16
Residual	92	2592.049	28.1744449		
Total	93	5442.584			

T Statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-4.44198	1.573046	- 2.823810966	0.005817627	-7.56619	-1.31778	-7.56619	-1.31778
CHM (m)	1.154738	0.114802	10.05855304	1.72088E-16	0.926732	1.382744	0.926732	1.382744

Shorea robusta

Regression Statistics	
Multiple R	0.77254
R Square	0.596818
Adjusted R Square	0.586984
Standard Error	5.088607
Observations	43

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1571.53	1571.53	60.69108	1.29E-09
Residual	41	1061.651	25.89393		
Total	42	2633.181			

T Statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-11.688	2.574372	-4.54015	4.86E-05	-16.8871	-6.489	-16.8871	-6.489
CHM (m)	1.740784	0.223451	7.790448	1.29E-09	1.289516	2.192053	1.289516	2.192053

Pinus roxbhurghii

Regression Statistics	
Multiple R	0.40926
R Square	0.167494
Adjusted R Square	0.095102
Standard Error	904.8832
Observations	26

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	3789001	1894501	2.313714	0.121466
Residual	23	18832714	818813.6		
Total	25	22621715			

T Statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-404.681	1027.763	-0.39375	0.697392	-2530.77	1721.408	-2530.77	1721.408
CHM (m)	-12.4302	54.59253	-0.22769	0.821899	-125.363	100.5031	-125.363	100.5031
CPA (m2)	71.13805	33.09385	2.149585	0.042341	2.678213	139.5979	2.678213	139.5979

Buchanania latifolia

Regression Statistics	
Multiple R	0.61482
R Square	0.378004
Adjusted R Square	0.067006
Standard Error	118.842
Observations	7

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	34332.75	17166.37	1.215454	0.386879
Residual	4	56493.72	14123.43		
Total	6	90826.47			

T statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-6.05885	170.0689	-0.03563	0.973288	-478.246	466.128	-478.246	466.128
CHM (m)	28.45243	20.37093	1.396717	0.235011	-28.1064	85.01121	-28.1064	85.01121
CPA (m2)	-13.1392	13.59813	-0.96625	0.388637	-50.8936	24.6153	-50.8936	24.6153

Terminalia alata

Regression Statistics	
Multiple R	0.357035
R Square	0.127474
Adjusted R Square	-0.30879
Standard Error	1522.625
Observations	7

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	1354848	677424	0.292196	0.761301
Residual	4	9273552	2318388		
Total	6	10628400			

T statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	832.4408	2470.899	0.336898	0.753128	-6027.88	7692.757	-6027.88	7692.757
CHM (m)	-4.28666	218.1932	-0.01965	0.985267	-610.088	601.5149	-610.088	601.5149
CPA (m2)	69.74517	134.7897	0.517437	0.632149	-304.491	443.9813	-304.491	443.9813

Annex 3: Regression, F Statistics, T Statistics of CHM and Tree height from field

Overall plots

Regression Statistics	
Multiple R	0.885124957
R Square	0.78344619
Adjusted R Square	0.781092344
Standard Error	2.714804695
Observations	94

Anova

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2453.061	2453.061	332.8367	2.55E-32
Residual	92	678.0551	7.370165		
Total	93	3131.116			

T statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.366767371	0.804548	-0.45587	0.64956	-1.96467	1.231135	-1.96467	1.231135
CHM (m)	1.071209582	0.058716	18.24381	2.55E-32	0.954594	1.187825	0.954594	1.187825

Shorea robusta

Regression Statistics	
Multiple R	0.933819
R Square	0.872017
Adjusted R Square	0.868896
Standard Error	1.292293
Observations	43

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	466.5296	466.5296	279.3554	6.57E-20
Residual	41	68.47089	1.670022		
Total	42	535.0005			

T statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.218193	0.653783	0.333739	0.740277	-1.10215	1.538534	-1.10215	1.538534
CHM (m)	0.948469	0.056747	16.71393	6.57E-20	0.833866	1.063072	0.833866	1.063072

Pinus roxbhurghii

Regression Statistics	
Multiple R	0.610212
R Square	0.372359
Adjusted R Square	0.346207
Standard Error	3.4658
Observations	26

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	171.0287	171.0287	14.23843	0.000932
Residual	24	288.2825	12.01177		
Total	25	459.3112			

T statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	5.500036	3.660702	1.502454	0.146025	-2.05528	13.05535	-2.05528	13.05535
CHM (m)	0.780815	0.206927	3.773384	0.000932	0.353739	1.207891	0.353739	1.207891

Buchanania latifolia

Regression Statistics	
Multiple R	0.814166
R Square	0.662867
Adjusted R Square	0.59544
Standard Error	1.359153
Observations	7

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	18.16065	18.16065	9.830931	0.025799
Residual	5	9.236488	1.847298		
Total	6	27.39714			

T statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.157135	1.797236	0.643842	0.548043	-3.46281	5.777077	-3.46281	5.777077
CHM (m)	0.714748	0.227958	3.135432	0.025799	0.128762	1.300734	0.128762	1.300734

Terminalia alata

Regression Statistics	
Multiple R	0.812672
R Square	0.660436
Adjusted R Square	0.592523
Standard Error	1.140961
Observations	7

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	12.65961	12.65961	9.724746	0.026298
Residual	5	6.508965	1.301793		
Total	6	19.16857			

T statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	13.56108	1.801078	7.529426	0.000654	8.931265	18.1909	8.931265	18.1909
CHM (m)	0.335355	0.107539	3.118452	0.026298	0.058917	0.611793	0.058917	0.611793

Annex 4: Regression, F Statistic, T Statistics of CPA and Tree Height from Field

Overall tree species

Regression Statistics	
Multiple R	0.728026
R Square	0.530022
Adjusted R Square	0.524913
Standard Error	3.999397
Observations	94

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1659.56	1659.56	103.7538	9.3E-17
Residual	92	1471.556	15.99518		
Total	93	3131.116			

T Statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	7.655531	0.698216	10.96442	2.19E-18	6.268814	9.042248	6.268814	9.042248
CPA (m2)	0.552197	0.054212	10.18596	9.3E-17	0.444528	0.659866	0.444528	0.659866

Shorea robusta

Regression Statistics	
Multiple R	0.764565
R Square	0.58456
Adjusted R Square	0.574427
Standard Error	2.328302
Observations	43

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	312.74	312.74	57.69058	2.41E-09
Residual	41	222.2605	5.420988		
Total	42	535.0005			

T Statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	8.075026	0.489758	16.4878	1.07E-19	7.08594	9.064111	7.08594	9.064111
CPA (m2)	0.344629	0.045373	7.595432	2.41E-09	0.252996	0.436262	0.252996	0.436262

Pinus roxbhurghii

Regression Statistics	
Multiple R	0.504335
R Square	0.254354
Adjusted R Square	0.223285
Standard Error	3.777585
Observations	26

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	116.8275	116.8275	8.186847	0.008608
Residual	24	342.4836	14.27015		
Total	25	459.3112			

T statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	12.99476	2.249822	5.775904	5.93E-06	8.351351	17.63816	8.351351	17.63816
CPA (m2)	0.391201	0.136723	2.861267	0.008608	0.109019	0.673384	0.109019	0.673384

Buchanania latifolia

Regression Statistics	
Multiple R	0.150565
R Square	0.02267
Adjusted R Square	-0.1728
Standard Error	2.314133
Observations	7

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.62109	0.62109	0.115979	0.74728
Residual	5	26.77605	5.355211		
Total	6	27.39714			

T Statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	7.185181	2.041061	3.520316	0.016913	1.938466	12.4319	1.938466	12.4319
CPA (m2)	-0.08823	0.259086	-0.34056	0.74728	-0.75424	0.577768	-0.75424	0.577768

Terminalia alata

Regression Statistics	
Multiple R	0.809334
R Square	0.655022
Adjusted R Square	0.586026
Standard Error	1.150021
Observations	7

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	12.55583	12.55583	9.493671	0.027433
Residual	5	6.612739	1.322548		
Total	6	19.16857			

T Statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	15.80047	1.129994	13.98279	3.36E-05	12.89572	18.70521	12.89572	18.70521
CPA (m2)	0.206316	0.06696	3.08118	0.027433	0.03419	0.378443	0.03419	0.378443