

## Repeat airborne laser scanning to assess canopy height changes in tropical montane forests

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### Abstract

Tropical montane forests are vital ecosystems globally, preserving biodiversity, carbon stocks, and capturing moisture. We employed two airborne laser scanning (ALS) data sets to study changes in montane forest canopy heights in the Taita Hills, Kenya between 2014/2015 and 2022. We studied two forests, Ngangao (129 ha) and Yale (57 ha), which encompassed both indigenous montane forest and exotic plantations. First, forest types were mapped using field observations and aerial imagery, and then, canopy height changes were analysed using canopy height models at spatial resolution (i.e. the cell size) ranging from 1 m to 20 m. The results revealed overall increase in canopy height in the studied forests, with considerable spatial variation between the forest segments and main tree species. Planted exotic tree species, particularly eucalyptus but also pine and cypress, exhibited faster growth rates than native tree species. Point density differences between the ALS data sets can cause bias to estimation of canopy height changes. However, we observed that reducing the cell size of the canopy height models from 1 m to 10 m and 20 m, decreased the positive trend between point density difference and overestimation of canopy height change due to higher point density of more recent ALS data set. These findings contribute to our understanding on spatial complexity of montane forest ecosystems dynamics and help informing forest monitoring and development of management strategies for fragmented forests in montane regions.

### 1. Introduction

Tropical montane forests (TMF) represent globally critical ecosystems that present diverse and complex interplay of environmental factors and rich biodiversity (Bruijnzeel et al., 2010). TMFs are characterized by varying topography, high levels of precipitation, and mist formation due to the interaction between lower altitude clouds and mountains. The presence of mist creates a moist microclimate, which contributes to the unique biodiversity. In addition to their ecological significance, TMFs play crucial roles in climate regulation, and act as reservoirs for water, providing constant stream flows and improving water quality (Martínez et al., 2009). Furthermore, TMFs are carbon-rich ecosystems with exceptionally high aboveground carbon stocks (Cuni-Sanchez et al., 2021).

Moreover, TMFs support the livelihoods of local communities by providing essential resources such as water, timber, and forest products. The forests also contribute to ecotourism, attracting visitors who seek to explore their diverse flora and fauna. However, despite their ecological and socio-economic importance, TMFs are increasingly threatened by human activities, including deforestation, land-use changes, and fragmentation (Cuni-Sanchez et al., 2021). Also, indigenous tree species can be replaced or mixed with plantations of exotic tree species, such as eucalyptus and pine (Pellikka et al., 2009). While fast growing, these plantations are less valuable ecologically and for the biodiversity. Therefore, there is a pressing need for effective monitoring methods and management strategies to conserve TMFs.

LiDAR (Light Detection and Ranging), in particular airborne laser scanning (ALS), is a well-established technique to collect 3D point clouds. Those can be analysed to produce digital terrain models, and to assess forest canopy structure and attributes, such as aboveground carbon stocks (Adhikari et al., 2017). When multitemporal, repeat ALS data are available, also changes in forest structure can be monitored (Zhao et al., 2016).

Repeat ALS data has great potential to provide insights into the ecological processes shaping TMFs and to assess the impacts of human activities on these ecosystems. Furthermore, it can facilitate the monitoring of forest restoration efforts and the evaluation of interventions to mitigate deforestation and habitat loss. However, such studies remain few as repeat ALS data has been only rarely collected over TMFs. Furthermore, quality of the ALS data sets from different year might differ, for example, in terms of flying height and point density, which can complicate interpretation of observed changes.

In this study, our main objective was to study changes in forest canopy height in the Taita Hills, Kenya using repeat ALS data. More detailed objectives were:

1. Assess canopy height changes in Ngangao and Yale forest fragments;
2. Compare canopy height change rates between indigenous montane forests and exotic plantations;
3. Evaluate impact of ALS point density variation on observed canopy height changes.

To reach these objectives, we analysed repeat ALS data from years 2014/15 and 2022, and prepared a forest type segmentation based on aerial imagery and field observations to study changes by forest type. By addressing these objectives, we seek to enhance our understanding on the dynamics of TMF ecosystems in the study area and contribute to their conservation and sustainable management.

### 2. Material and methods

#### 2.1 Study area

The studied forests are located in the Taita Hills, Taita-Taveta County, Kenya, approximately 150 km from the Indian Ocean (Fig. 1). Covering an area of about 1000 km<sup>2</sup> with an average elevation of 1500 meters, the Taita Hills experience a unique

climate influenced by the Intertropical Convergence Zone and the nearby Indian Ocean (Pellikka et al., 2013). Rainfall, occurring in two seasons - long rains between March and June and short rains between October and December - varies annually, with significant differences observed between the plains and the hills, where annual rainfall can exceed 1200 mm. This moisture, originating from the Indian Ocean, interacts with the rising hills, leading to mist and cloud precipitation throughout the year (Pellikka et al., 2013). The Taita Hills form part of the Eastern Arc Mountains (EAM), a mountain chain stretching from Eastern Tanzania to Southern Kenya, renowned for its biodiversity and numerous endemic species (Burgess et al., 2007). Despite the ecological significance, the Taita Hills have experienced significant forest loss, with up to 50% of indigenous forest areas disappearing between 1955 and 2004 due to agricultural expansion and human population growth. The remaining forest patches face ongoing threats from agricultural encroachment and exotic tree species, such as cypress, eucalyptus, and pine, introduced for commercial purposes since the 1950s (Pellikka et al., 2009).

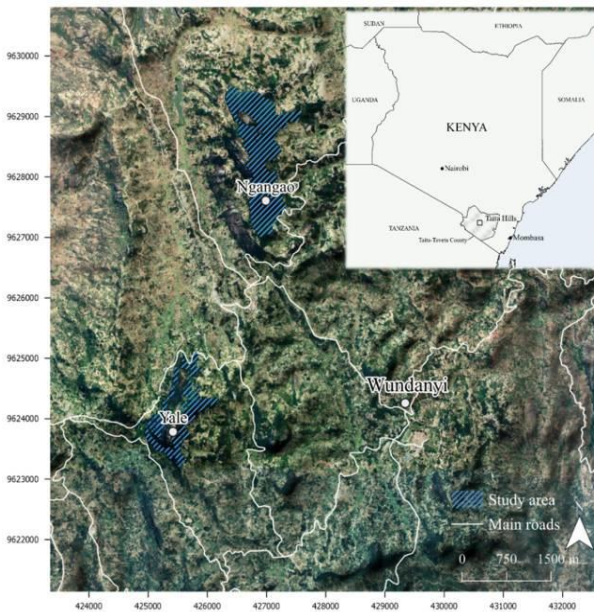


Figure 1. Location of study area, Ngangao and Yale forests, in Taita-Taveta County, Kenya (Google Satellite Imagery 2020 © CNES / Airbus & © Maxar Technologies).

We focused on two forest fragments in the Taita Hills, Ngangao and Yale, which are both subject to human-induced changes. Ngangao locates on the eastern slope of a north-south oriented mountain ridge (Pellikka et al., 2009). This drier lower montane forest has multi-layered canopy and it is composed of indigenous forest and planted exotic forest patches (Adhikari et al., 2020). Ngangao's altitude ranges from 1700 m to 1952 m. Yale is located on a north-south oriented mountain ridge and it has large areas of bare rock and heathland (Pellikka et al., 2009). Remaining native montane forest patches are small compared to Ngangao and area of exotic plantations. The altitude varies from 1750 m to 2104 m. Both Ngangao and Yale are gazetted forests. Some typical indigenous tree species in the montane forests include *Tabernaemontana stapfiana*, *Macaranga conglomerata*, *Albizia gummifera*, *Oxyanthus speciosus*, *Xymalos monospora* and *Celtis africana* (Amara et al., 2023; Pellikka et al., 2009).

## 2.2 Airborne laser scanning (ALS) data

We employed two discrete return ALS data sets (Table 1). The first (ALS1) was based on the scanings completed during two years, early 2014 and early 2015 (Adhikari et al., 2020). The second (ALS2) was collected seven years later, in early 2022. Both data sets were scanned using the same Leica ALS60 sensor. A maximum of four returns per pulse were recorded. However, the resulting point densities differed because of the difference in flying altitude, and hence, the more recent data set had higher point density and smaller footprint (Table 1). Both data sets were pre-processed by the data vendor and delivered as georeferenced point clouds in UTM projection and WGS84 reference system with ellipsoidal heights.

Attribute	ALS1	ALS2
Acquisition year	2014 and 2015	2022
Sensor	Leica ALS60	Leica ALS60
Mean flying height AGL (m)	1460	800
Mean footprint size (cm)	32	18
Pulse rate (kHz)	58	99
Scan rate (Hz)	66	59
Scan angle (°)	±16	±20
Mean point density (points m <sup>2</sup> )	5.7	11.3

Table 1. Summary of the ALS data sets.

## 2.3 ALS data processing

We employed LAsTools software (rapidlasso, 2022) to generate elevation models at 1 m cell size for both ALS1 and ALS2 data sets. The classification of points into ground and non-ground classes was performed using lasground\_new using parameters optimized through experimentation (step size 10). Given the multi-layered, dense forest cover in the studied forests, finding bare ground points posed a challenge. To address this, we combined ground points from both ALS data sets, which is similar to earlier studies using repeat ALS data for change detection (Nunes et al., 2021; Riofrío et al., 2022). Then, a digital terrain model (DTM) with a 1 m cell size was created using the combined ground points and the blast2dem tool. The option 'thin\_with\_grid 0.5' was used to equilibrate differences in point density before TIN generation.

Next, we generated canopy height models (CHMs) at 1 m cell size using two different approaches - one using spike-free and the other using pit-free method - for comparative analysis. For CHM production, we thinned point clouds to constant point density using lasthin tool, retaining only the highest point per 0.5 m cell. The spike-free method (Khosravipour et al., 2016) is executed during digital surface model (DSM) creation using las2dem and it utilize all returns instead of just first returns to reduce spikes in the TIN. CHM is then created by subtracting the DTM from the DSM. Conversely, the pit-free method (Khosravipour et al., 2014) employs height-normalized points and partial CHMs at various thresholds to mitigate pits and enhance CHM quality. For generating the pit-free CHM, ground normalised elevations were generated with lasheight and combined ground points.

## 2.4 Canopy height change detection

The resulting CHMs were visualized and analysed in QGIS and R software environment to assess canopy height changes

between the two data sets and forests. Canopy height model change (CHMC) was calculated using both the spike-free and pit-free CHMs. The CHMs from 2014/15 were subtracted from the 2022 CHMs. The elevation models express the height difference between the CHMs. Simple Filter with the smoothing option in QGIS was applied to the spike-free CHMC raster at 1 m cell size to reduce noise. Finally, based on the visual analysis of the change detection results, we selected pit-free CHMs for further analyses. Only those results are reported later.

### 2.5 Sensitivity of canopy height change to point density difference

ALS1 point density was on average smaller than that of ALS2, which can cause bias to estimation of canopy height changes (Nunes et al., 2021). However, because of spatial variation in point density, in some area, point density in ALS2 might be higher than in ALS1. Whatever the case, when calculating CHMC, the values might be over- or underestimates of canopy height change because of the difference. To tackle this, we studied how CHMC depends on the point density difference. We did the analysis by comparing CHMC and point density difference at 1 m, 2 m, 5 m, 10 m, 20 m and 30 m cell size similar to the analysis by Nunes et al. (2021). The spatial resolution was lowered by aggregating 1 m cells to coarser cell size. After selecting the spatial resolution based on the sensitivity analysis, we created CHMC layers for the further analysis at 10 m and 20 m cell size. These layers were done in QGIS using resampling -tool with weighted means.

### 2.6 Forest type segmentation

In order to study CHMC by forest type, we segmented forest types in QGIS, primarily relying on visual interpretation of false-colour aerial imagery with a 10 cm cell size. Ground reference data on forest types was collected 22–26 January 2022 in Ngangao (85 points) and Yale (47 points) using GNSS devices. Furthermore, an earlier segmentation of Ngangao and Yale by Adhikari et al. (2020) was used as a baseline. The segments were digitized based on clear boundaries identified in the images. Notably, distinct features observed in the imagery, for example, unique canopy formations of certain tree species, such as pine, exhibiting crown shyness, aided in the segmentation process. Moreover, recognizable features such as distinct tree plantation areas, for example, eucalyptus plantations, were identified in the CHM due to their similar heights.

To capture potential CHMC trends across different parts of the Ngangao forest, we divided the montane forest part of the forest into four segments: northwest, north, middle, and south. This division aimed to delineate areas with potentially different CHMC patterns and facilitate a more detailed analysis of the forest dynamics.

Forest type distribution differs substantially between the two forests (Fig. 2). Ngangao has mostly indigenous montane forest with small segments of exotic forests: pine, cypress, and eucalyptus (Table 2). The indigenous montane forest dominate and covers the area from north to south. Based on the segmentation, its area is 118.5 ha.

Yale is more patched and consists of smaller segments (Table 3). Indigenous montane forest is only left in a few parts of the forest whereas eucalyptus dominates the area, especially, in the western and southern part of the mountain. Eastern part has

more variance as there are different types of forests with smaller area. There are also areas of mixed forest, where it was not possible to differentiate the dominant tree species based on the material used. Those areas could include both indigenous and exotic tree species, or just exotics. The area of indigenous montane forest in Yale is estimated as 7.2 ha.

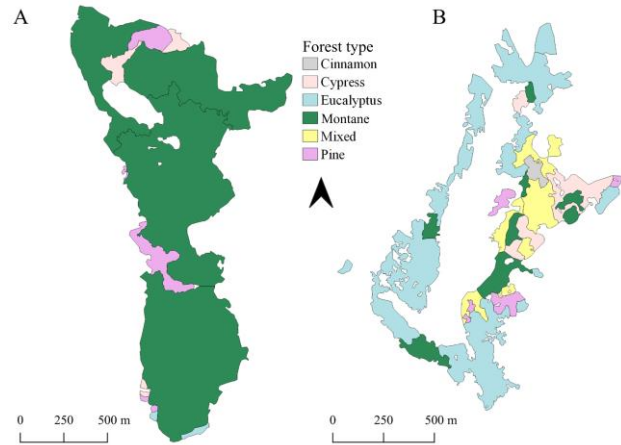


Figure 2. Forest types in (A) Ngangao and (B) Yale forests.

Forest type	Area (ha)	Area (%)	Number of segments	Range of area (ha)
Montane	118.5	91.6	4	14.4–43.2
Eucalyptus	0.7	0.5	2	0.2–0.5
Pine	6.8	5.3	5	0.1–4.0
Cypress	3.3	2.6	3	0.3–1.9
Total	129.3	100	14	0.1–43.2

Table 2. Forest type statistics for Ngangao forest.

Forest type	Area (ha)	Area (%)	Number of segments	Range of area (ha)
Montane	7.2	12.6	8	0.3–1.8
Eucalyptus	33.2	58.3	10	0.2–10.0
Pine	2.3	4.0	5	0.2–1.1
Cypress	5.4	9.5	3	0.5–3.3
Mixed	8.0	14.0	6	0.3–3.1
Cinnamon	0.9	1.6	1	0.9
Total	57.0	100	33	0.2–10

Table 3. Forest type statistics for Yale forest.

## 3. Results

### 3.1 Canopy height models

The CHMs revealed differences in canopy heights between Ngangao and Yale as notable in the CHMs for 2022 (Fig. 3). Yale exhibits a higher proportion of taller canopies, particularly in the areas dominated by eucalyptus. Within Ngangao, there is variation in canopy height between the indigenous montane forest segments, with taller forest found in the southern part and lower forest in the northwestern part.

When comparing the canopy height distributions between the two data sets (Fig. 4), the difference in canopy heights is more noticeable in Yale where heights show apparent increase compared to Ngangao with greater cover of indigenous species.

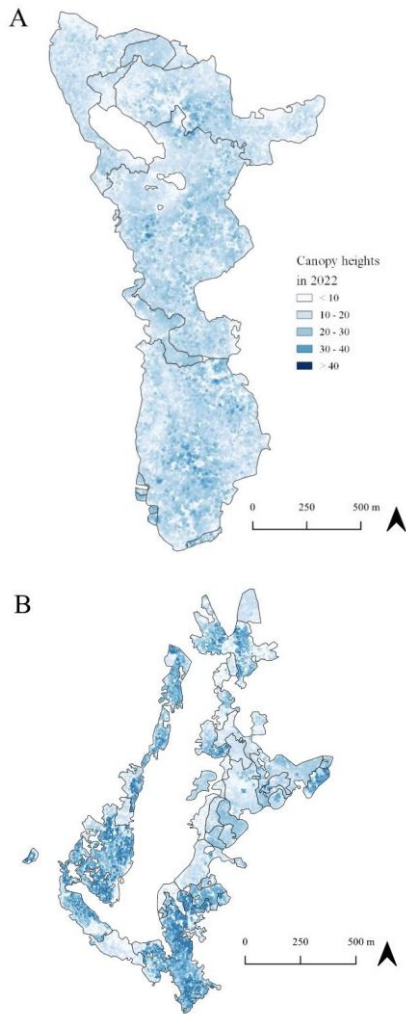


Figure 3. Canopy height model of (A) Ngangao and (B) Yale at 1 m cell size for 2022.

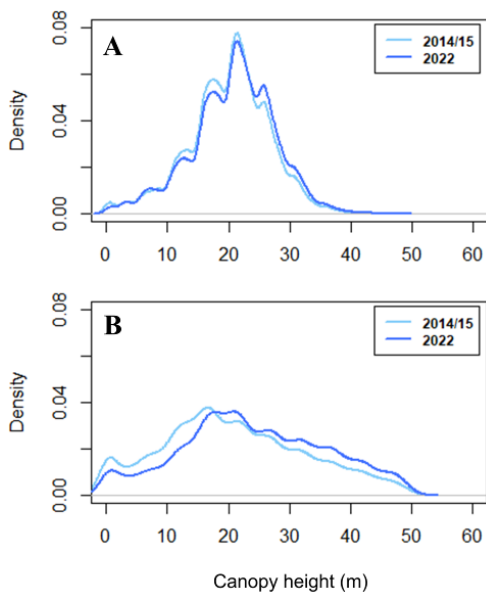


Figure 4. Density distribution of canopy heights in (A) Ngangao and (B) Yale in 2014/15 and 2022.

### 3.2 Impact of variable point density on observed canopy height changes

Point density varied between the two ALS data sets on average but also spatially as shown in Fig. 5. To mitigate uncertainties in CHMC due to variable point density, we studied how CHM spatial resolution affect to the observed changes. Coarsening of the cell size reduced extreme values. As a result, the standard deviation of CHMC reduced from 5.3 m to 2.2 m when cell size was decreased from 1 m to 30 m. When analysing the relationship between CHMC and point density difference, a clear positive trend was revealed at finer cell sizes of 1 m, 2 m and 5 m (Fig. 6). In other words, when the point density of the more recent data set was greater, observed CHMC was also greater, indicating possible bias. However, at 10 m and 20 m cell sizes, the trend could not be observed, indicating more stable results for subsequent analyses.

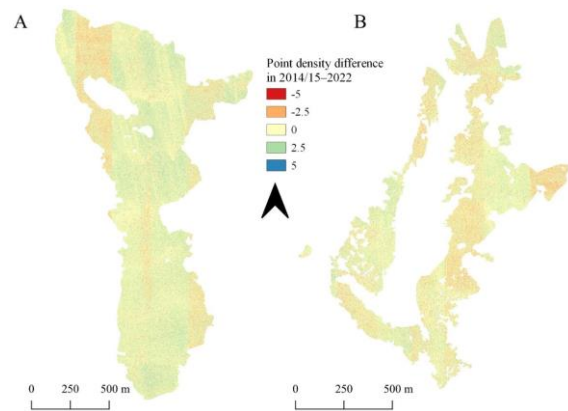


Figure 5. Difference in point density between ALS data sets in (A) Ngangao and (B) Yale.

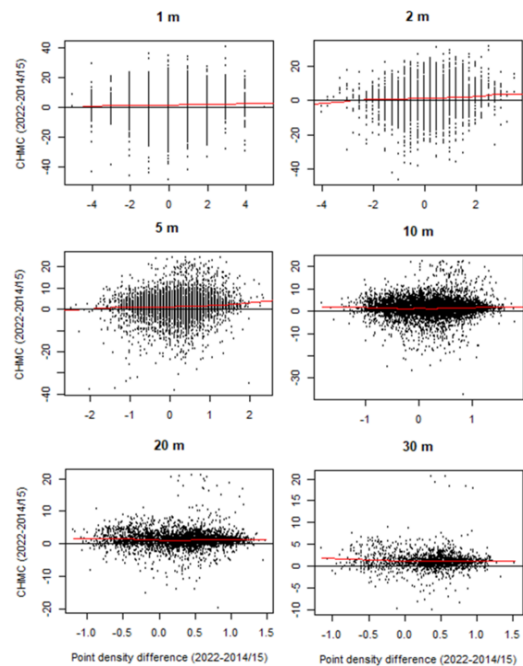


Figure 6. Relationship of point density difference between ALS2 and ALS1 and canopy height model change (CHMC) at different cell sizes (1 m – 30 m).

### 3.3 Canopy height model changes

Based on the results above, we used 10 m cell size for the later analyses. That cell size reduce the details but still contains adequate information about spatial variation and forest gaps. The results differed only little between 10 m and 20 m cell sizes, further justifying the use of fine spatial resolution (20 m results not shown here).

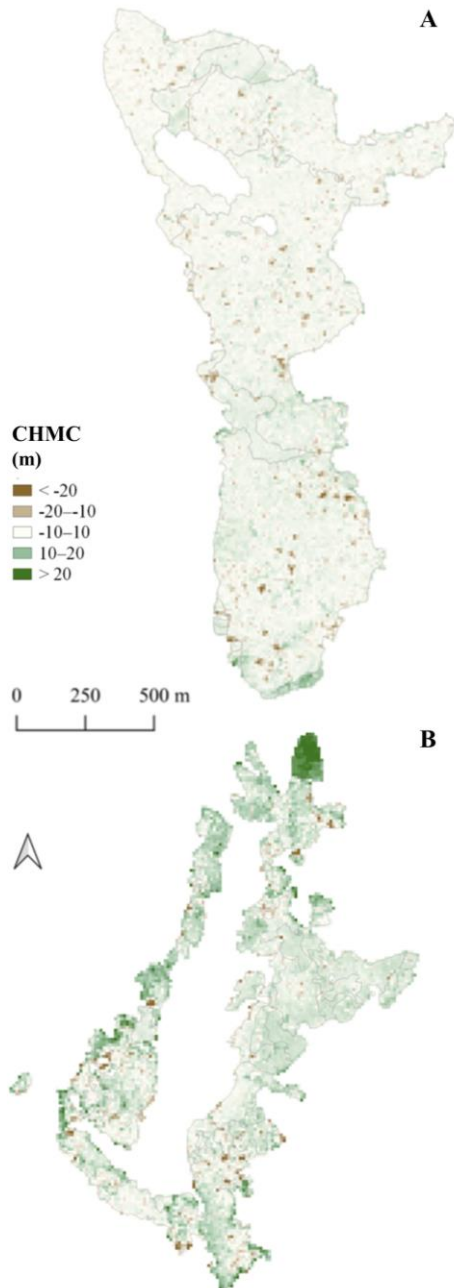


Figure 7. Canopy height model change (CHMC) between ALS1 and ALS2 at 10 m cell size in (A) Ngangao and (B) Yale.

Fig. 7 display the final CHMC maps for the studied forests. Yale with greater human influence and presence of exotic plantations has been clearly more dynamic during the studied period than more stable Ngangao, with greater cover of indigenous forest. Notable features in the CHMC maps include

eucalyptus plantations in northern Yale and southern Ngangao showing the greatest tree growth rates in the 7–8 years period. Negative changes, mostly indicating treefall gaps, are evenly distributed, particularly in Ngangao.

The violin plot in Fig. 8 shows the distribution of CHMC for by forest types. The width represents the data density. Narrow ends correspond to only a few or single values and might be errors. The black rectangles describe quartiles and the white dots are median values. All medians are above zero, which implicates growth in all forest types.

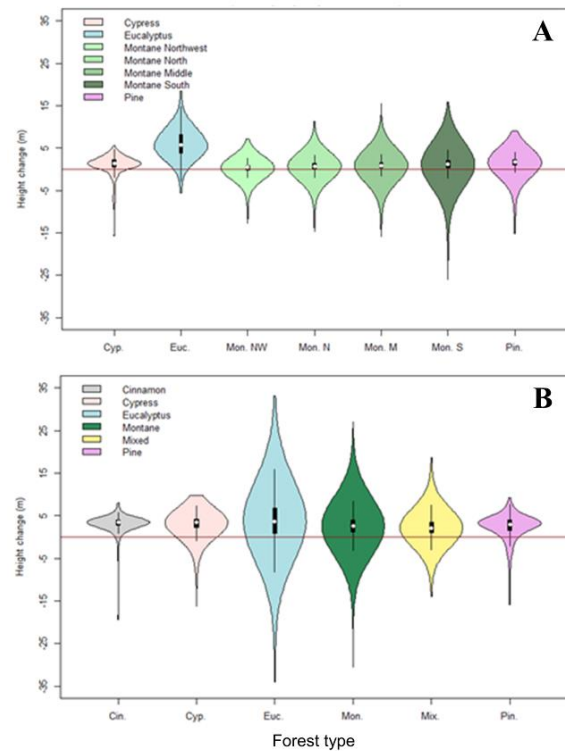


Figure 8. Distribution of the canopy height changes between different forest segments at 10 m cell size in (A) Ngangao and (B) Yale.

Based on Fig. 7 and Table 4, it is evident that eucalyptus forests show the fastest growth. In Ngangao, eucalyptus stands out as most of the changes are positive and the values highest. Indigenous montane forests in Ngangao has more even distribution of positive and negative values but the median values are still positive. The mean and median values for indigenous montane forests are the smallest among all the forest types in Ngangao (Table 4). The patterns remained similar even when negative changes corresponding to the treefall gaps were removed from the analysis.

In Yale, eucalyptus forests have a very wide range of both positive and negative values but the median and mean are still the highest among the forest types (Table 4). Large negative values might correspond to logging activities in the western parts of Yale. Similar to Ngangao, indigenous montane forests have the lowest median and mean values.

Forest/ Forest type	Median (m)	Mean (m)
Ngangao		
Cypress	1.37	1.09
Eucalyptus	5.79	6.06
Montane (NW)	0.46	0.20
Montane (N)	0.77	0.54
Montane (Middle)	0.97	0.70
Montane (S)	1.24	0.78
Pine	1.67	1.26
Yale		
Cinnamon	3.47	3.08
Cypress	3.42	2.94
Eucalyptus	3.61	3.78
Montane	2.11	2.25
Mixed	2.66	2.52
Pine	3.00	2.29

Table 4. Median and mean canopy height model change by forest type for Ngangao and Yale. Indigenous montane forest was analysed separately for four parts in Ngangao.

#### 4. Discussion

We investigated canopy height changes in Ngangao and Yale, which are two forest areas in the Taita Hills, Kenya, within the Eastern Arc Mountains biodiversity hotspot. While forest cover changes have been extensively studied (Pellikka et al., 2009; Pellikka et al., 2018; Wekesa et al. 2019), little attention has been given to forest height changes in TMFs in Africa.

Repeat ALS data from 2014/15 and 2022 revealed an overall positive CHMC trend between the ALS acquisitions (7–8 years), indicating forest height growth. This is positive result as negative changes could indicate forest degradation. The fastest growth rates were observed in young eucalyptus forest in Yale, while taller and older plantations of cypress and pine showed smaller growth rates. However, the lowest growth rates were observed consistently for indigenous montane forest type. Further research is needed to study how growth rates depend on tree age in different forest types.

The point density differed between the data sets on average but also spatially. Our results showed that comparison of high spatial resolution CHMs (cell size < 10 m) overestimated change as larger positive changes were observed when more recent data set had greater point density than older data set. This has been observed also earlier (Zhao et al., 2018; Nunes et al., 2021). Higher point density increases the probability that the highest part of the crown is hit by laser pulse. Here, we were able to reduce the effect by lowering the cell size of the CHMs. As repeat ALS data sets remain scarce, novel approaches to mitigate point density differences are required.

Furthermore, tree growth is also not just vertical, and lateral growth of crowns can affect results by causing overestimation of height changes (Senécal et al., 2018). Individual tree detection based methods and direct comparison of point clouds could be studied as alternatives for CHM based approach to reduce both problems. Field based tree height monitoring in permanent plots could be also useful for calibrating change detection models.

#### 5. Conclusions

Our study provides valuable insights into canopy height changes and variations in TMF human modified landscapes with forest plantations. Repeat ALS data proved useful, but future studies should consider the various uncertainties and factors affecting the results. Further research with more detailed forest type analysis could provide deeper understanding for sustainable forest management in the Taita Hills. Overall, our findings advance our comprehension of the spatial complexity of forest ecosystem dynamics, offering valuable insights for forest monitoring and the development of management strategies.

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