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Changes in agroforestry in the Taita Hills, Kenya, based on multitemporal airborne laser scanning data

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Abstract

Agroforestry is a collective name for agricultural land-use practices where combinations of woody perennials such as trees and shrubs are intentionally managed with crops and/or livestock in same land units for various environmental and economic benefits. As a sustainable farming practice, agroforestry is used to increase food production without adding harmful impacts of agriculture on natural environment. Agroforestry is a common farming practice in Taita Hills, Kenya, where it is motivated by Kenyan policies supporting tree planting in the fields. This study aims to find out how canopy height and canopy cover have changed during the last ten years in the croplands of Taita Hills to get more knowledge on the state and trends of agroforestry in the study area.

Changes in canopy height and canopy cover in croplands are approached by multitemporal airborne laser scanning (ALS) data. ALS is an active remote sensing method used to acquire three-dimensional point cloud data of a target landscape. Canopy height models (CHM), 99th percentile canopy height and canopy cover data were derived from two ALS data sets from 2014/2015 and 2022 and used for the change detection of canopy height and canopy cover during the study period. Field data from 2013 and 2022 containing tree measurements from 28 field plots were used in the validation of ALS-based analyses.

The results indicate that there has been a slight increase in canopy height and canopy cover during the study period. It is acknowledged that the study period is quite short to detect changes in tree growth. Hence, only slight positive changes in canopy height and canopy cover were expected. Based on CHM changes, almost 20% of the area outside forests had ≥ 2 m increase in the canopy height. Furthermore, 7% of the area outside forests had ≤ -5 m decrease in the canopy height, which corresponds to tree loss. Results for CHM based canopy height were supported by 99th percentile canopy height changes. The area outside forest with ≥ 10% canopy cover increased from 67.4% to 68.0%. Even though canopy height and canopy cover had a slight increase in the croplands, forest cover was detected to be increasing during the study period.

ALS and field measurements matched well with each other. In the tree height measurements, there were more variance with taller trees, probably caused by difficulties in measuring taller trees in the field. Moreover, ALS data was found to underestimate tree height changes. The average absolute deviation for tree height changes was 1.3 m shorter for ALS-measured tree heights than field measurements. Number of trees in field plots has mainly decreased during 2013–2022. ALS-based mean canopy height and canopy cover changes in the plots explain the actual changes well if large number of trees have been cut down during the study period.

The thesis provides valuable information on the state and trends of agroforestry in Taita Hills. However, more exact land cover classification could have enhanced the accuracy of the results even more. All in all, the results were mainly positive, indicating that there has been an increasing trend in canopy height and canopy cover in the croplands in Taita Hills.

Keywords

Agroforestry, change detection, multitemporal airborne laser scanning, remote sensing, canopy height, canopy cover, Taita Hills

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Tiivistelmä

Peltometsäviljelyksi kutsutaan maankäyttömuotoja, joilla puuvartisia kasveja kuten puita ja pensaita ylläpidetään samoilla maa-alueilla viljelyskasvien ja/tai kotieläinten kanssa. Peltometsäviljelyä harjoitetaan erilaisten ympäristöllisten ja taloudellisten etujen vuoksi. Se on kestävä maatalousmuoto, jota käytetään tehostamaan ruoantuotantoa ilman, että maatalouden haitalliset seuraukset ympäristölle lisääntyvät. Peltometsäviljely on yleinen maatalousmuoto Taitavuorilla, Keniassa, jossa paikalliset linjaukset kannustavat puiden istuttamiseen pelloille. Tämän tutkimuksen tavoitteena on selvittää, kuinka paljon latvuston korkeus ja peittävyys ovat kasvaneet Taitavuorten viljelysmailla viimeisten kymmenen vuoden aikana. Tulosten avulla voidaan saada lisää tietoa peltometsäviljelyn nykytilasta tutkimusalueella.

Latvuston korkeuden ja peittävyyden muutosten tutkimuksessa hyödynnetään moniaikaista lentolaserkeilausta. Lentolaserkeilaus on aktiivinen kaukokartoitusmenetelmä, jolla saadaan kerättyä kolmiulotteista pistepilvidataa tutkittavasta kohteesta. Latvuston korkeuden ja peittävyyden muutostulkinnassa käytettiin laserkeilausaineistoista johdettuja latvuksen korkeusmalleja, latvuston korkeutta 99. prosenttipisteessä ja latvuston peittävyysaineistoja vuosilta 2014/15 ja 2022. Kenttäaineistoa vuosilta 2013 ja 2022 käytettiin laserkeilausanalyysien validoinnissa.

Tulokset osoittivat hienoisen kasvun latvuston korkeudessa ja peittävyydessä. Tutkimusjakson todettiin olevan suhteellisen lyhyt, jotta huomattavia muutoksia latvuston korkeudessa ja peittävyydessä olisi mahdollista havaita. Tämän takia hienoinen kasvu tutkittavissa muuttujissa oli odotettavissa. Lähes 20 % metsien ulkopuolisesta alueesta oli kasvanut yli 2 m tutkimusjakson aikana. Lisäksi 7 %:lla metsien ulkopuolisesta alueesta latvuston korkeus oli vähentynyt yli 5 m. Tämä tulkittiin puuston katoamiseksi. Latvuston korkeus 99. prosenttipisteessä tuotti samankaltaisia tuloksia kuin latvuston korkeusmalli. Metsien ulkopuolisella alueella yli 10 % peittävyys kasvoi 67.4 %:sta 68.0 %:iin. Siitäkin huolimatta, että latvuston korkeuden ja peittävyyden havaittiin kasvaneen, metsien peittävyys väheni tutkimusjakson aikana.

Laserkeilaus- ja kenttämittaukset olivat hyvin samansuuntaisia. Kentällä mitattujen korkeiden puiden pituuksissa havaittiin vaihtelua, minkä tulkittiin johtuvan mittausvaikeuksista. Laserkeilausdatan havaittiin lisäksi aliarvioivan puuston korkeuksia. Kentällä mitattujen puuston korkeuksien keskimääräinen absoluuttinen poikkeama (AAD) oli 1,3 m suurempi kuin laserkeilausmittausten vastaava luku. Puiden määrä tutkimuspisteillä oli pääosin vähentynyt vuosien 2013 ja 2022 aikana. Laserkeilausdatasta johdetut latvuston korkeuksien ja peittävyyksien muutokset selittivät todellisia kenttäkohteilla tapahtuneita muutoksia, jos suuri osa tutkimuspisteen puista oli kaadettu tutkimusjakson aikana.

Tämä tutkielma tarjoaa arvokasta tietoa peltometsäviljelyn tilasta Taitavuorilla. Tarkempi maatalousluokittelu olisi kuitenkin voinut parantaa tulosten tarkkuutta entisestään. Kaiken kaikkiaan saadut tulokset olivat pääosin positiivia ja viittasivat latvuston korkeuden ja peittävyyden kasvuun Taitavuorilla.

Avainsanat

Peltometsäviljely, muutostulkinta, moniaikainen lentolaserkeilaus, kaukokartoitus, latvuston korkeus, latvuston peittävyys, Taitavuoret

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1 Introduction

Global demand for food has been expected to be growing as global population and wealth are increasing (Godfray et al., 2010). Increasing demand for food is mainly taking place in developing countries (Dar & Twomlow, 2007). In Sub-Saharan Africa, the increases in food production are reached by taking more land under agricultural use (Pellikka et al., 2013). Agricultural land has grown 28% at the expense of natural vegetation, especially forests, between 1990 and 2010 in East Africa (Brink et al., 2014). Intensive agriculture already has major impacts on natural environments: it is responsible for over third of human caused carbon dioxide, methane and nitrous oxide emissions (Foley, 2011), nitrogen fertilizers used in agriculture are harmful for terrestrial and aquatic ecosystems (Vitousek et al., 1997) and it threatens biodiversity by causing habitat loss and fragmentation (Dirzo & Raven, 2003). While the demand for food is increasing, more sustainable ways to increase food production needs to be adopted.

Sustainable farming practices, such as agroforestry, can be used to intensify agriculture and increase the yields sustainably without causing additional harm to the environment (Pretty et al., 2011). Agroforestry is a collective name for agricultural land-use practices where combinations of woody perennials such as trees and shrubs are intentionally managed with crops and/or livestock in same land units in some sort of spatial arrangements and/or temporal sequences (Nair, 1991). Agroforestry has several environmental, social and economic benefits and it can reduce the harmful impacts of agriculture on natural environment (Wilson & Lovell, 2016). On top of that, FAO (2022) determines agroforestry as one of the tree- and forest-based solutions to global socio-economic and environmental challenges.

For its several benefits for environment and smallholder, multitemporal changes in agroforestry are relevant to be studied to get more understanding about the state of agroforestry in a specific region. This information of a state of agroforestry can be forwarded to decision makers to give them feedback on how their agricultural policies are acting (Atzberger, 2013). Change detection is an analysis method used to detect multitemporal changes in a landscape from at least two different time points (Singh, 1989). For example, it can be used to detect changes in agroforestry and canopy height and canopy cover in croplands. Tree height is one of the essential tree attributes used to predict other tree attributes such as carbon stocks, biomass and the age of the tree (Wang et al., 2019). Taller trees stock more carbon, hold more biomass and are usually older than shorter trees in the same site. Tree cover in agricultural lands, on the other hand, can be used to estimate the extent of agroforestry and how much benefits it provides in the surrounding areas (FAO, 2022). Therefore, these two attributes are further focused on this study.

Tree growth is a three-dimensional process (Eitel et al., 2016) which can be detected using laser scanning. Laser scanning is a remote sensing method used to acquire three-dimensional point data of a specific target, such as landscape. It utilizes laser scanner's own light source to measure the x-, y- and z-coordinates of a target in a relation to the laser scanner's sensor to produce three-dimensional point clouds to represent scanned surfaces (Eitel et al., 2016; Holopainen et al., 2013). Airborne laser scanning (ALS), operated from aerial platforms, can be used to detect high-accurate regional data of topography, vegetation structures and forest attributes, to study tree height growth and to produce canopy height models of scanned surface (Eitel et al., 2016; Heiskanen et al., 2015; Holopainen et al., 2013; Okyay et al., 2019; Yu et al., 2006). In this study, ALS is utilized to get three-dimensional data of tree cover and agroforestry in the Taita Hills.

Agroforestry is a common agricultural practice in tropics and developing countries (Skole et al., 2021) and in 2020, 28% of total area of agroforestry was in Africa (FAO, 2022). It is also common agricultural practice in Taita Hills, Kenya, where it has been motivated by Kenyan policies supporting tree planting in the fields as one of the actions used to reach national tree cover of 10% by 2022 (Republic of Kenya, 2019). Groups of trees or individual trees outside forests, for example in the agricultural landscapes, can also be called trees outside forests (FAO, 2020). Thus, trees outside forests could be alternative definition than agroforestry to describe the land use type in Taita Hills. Trees outside of forests include different land use systems with sparse tree cover or tree production, such as agroforestry (Skole et al., 2021). Classifying agroforestry land use practices using remote sensing and ALS is difficult (Piiroinen et al., 2015). Thus, in this study agroforestry is used to refer to trees outside of forest since majority of the area outside forests in Taita Hills is covered by cropland and agroforestry.

Tree cover in agricultural lands has been increasing globally since early 2000s (Zomer et al., 2016). Prior studies have also widely examined the changes of woody vegetation in Taita Hills. Even though the area of indigenous forests have been decreasing since 1950, the amount of woody vegetation has been increasing due to tree planting for example for agroforestry purposes (Pellikka et al., 2009). Thus, tree cover in croplands have been increasing since late 1900s (Pellikka et al., 2018). Teucher et al. (2020) reported that croplands have been abandoned in hills leading to increases in bushland and tree cover. However, changes in agroforestry have not been studied recently. Considering the benefits of agroforestry and tree cover in biodiversity conservation, detecting changes in agroforestry regularly is beneficial especially as Taita Hills are one of the 25 biodiversity hotspots in the world (Myers et al., 2000). Endemic species inhabiting Taita Hills are already threatened by extinction (Githiru et al., 2011) and agricultural expansion threatens to decrease biodiversity (Pellikka et al., 2013). Taita Hills were selected as a study area in this research due to its unique nature and high availability of data but lack of research in the changes of agroforestry.

This thesis focuses to study changes in agroforestry in the Taita Hills, Kenya, based on multitemporal ALS data. The main research question is to find out how canopy height and canopy cover have changed during 2014/15–2022 in the croplands. Have canopy height and canopy cover increased or decreased during the study period? This question is answered by detecting changes in canopy height and canopy cover between 2014/15 and 2022 based on ALS data. Field measurements from 2013 and 2022 are used in the validation of ALS-based analyses. The results can be used to achieve better understanding and new knowledge about the state and trends of agroforestry in the study area. This research is part of and funded by the ESSA project for Climate-smart Agropastoral Ecosystem Transformation in East Africa which is funded by the DeSIRA programme of the European Union in 2020–2024.

2 Background

2.1 Agroforestry

2.1.1 Defining agroforestry

Agroforestry is a collective name for land-use systems and practices, which intentionally combine trees and other woody perennials with crops and/or livestock on the same land use units in some sort of spatial arrangement and/or temporal sequence (FAO, 2022; Lundgren & Raintree, 1983; Nair, 1991). The interactions of these agroforestry components in the same spatial units can provide environmental benefits in the surrounding areas and economic benefits for smallholders (Gassner & Dobie, 2022). Phrase 'agroforestry' is often described as 'a new word for an old practice' (Lundgren & Raintree, 1983; Nair, 1991, 1993) meaning that agroforestry is old and traditional farming practice, even though farming practices combining trees with agriculture have only recently gotten a collective name to call them.

Several characteristics can be seen to be common for all agroforestry systems. At least two species of plants are managed in agroforestry systems out of which at least one is always a woody perennial (Lundgren & Raintree, 1983). Thus, agroforestry systems have always at least two outputs: crops or animals and tree products (Nair, 1993). In addition, cycle of agroforestry systems is always more than a year (Lundgren & Raintree, 1983). Involving trees with agricultural practices makes agroforestry systems remarkably different than the conventional farming systems: agroforestry systems with the simplest structure and composition of agricultural components are still ecologically, structurally and economically more complex than farming systems based on monoculture (Lundgren & Raintree, 1983; Nair, 1991).

Agroforestry systems do not look same everywhere. Different types of agroforestry systems are categorized based on the composition of agricultural components (trees, crops, livestock) and based on their arrangement in space and/or time in the croplands (Nair, 1991). The type of agroforestry adopted in the region depends on the environmental, agroecological and socio-economical characteristics that define what kind of practices are most suitable in the specific region (Mbow et al., 2014). Typical agroforestry landscape in Taita Hills is shown in Figure 1.


Figure 1. Agroforestry landscape in Taita Hills (Elli-Nora Kaarto, 2022).

2.1.2 Benefits for natural environment

Since agricultural intensification, large-scale farming and monoculture, change the natural functionality of ecosystems (Lin et al., 2008), adopting agroforestry practices and restoring agroecosystems can increase the supply of supporting and regulating ecosystem services (Barral et al., 2015). It has been shown that even crop yields can be increased by adopting agroforestry practices without having negative impact on regulating ecosystem services (Kuyah et al., 2019). In other words, agroforestry helps to maintain ecological balance of the environment (Aryal et al., 2019).

Agroforestry is an effective climate change mitigation option (Skole et al., 2021). It has an important role in carbon sequestration since agroforestry systems can sequester and store carbon on both aboveground and belowground biomass (Nair, 2012). In addition, compared to simple monocropping and pasture systems, agroforestry systems have greater potential to sequester carbon since agroforestry systems have ability to utilize more growth resources like light, nutrients and water (Nair, 2011). However, it is worth to notice that not all agroforestry systems have similar abilities to sequester carbon since it depends on several factors such as the region of the agroforestry system, the type of the species and the previous land-use on the site (Nair, 2012).

By increasing the number of trees in the croplands, agroforestry improves soil health in many ways by reducing soil erosion, increasing soil organic carbon and increasing nutrient availability and nitrogen storages in the soil (Gassner & Dobie, 2022; Muchane et al., 2020). Nitrogen fixing trees, which are commonly used in the agroforestry systems in the tropics, are especially important in increasing nitrogen inputs in the soil (Jose, 2009; Nair, 2011). Agroforestry can also increase water retention by capturing water in the soil (Pretty et al., 2011) and enhance water quality by decreasing erosion caused sediment load and additional nutrient runoffs on waters (Foley et al., 2005). Nutrient runoffs are greater in intensive farming systems, which usually lean on the use of fertilizers and other chemicals. Agroforestry is also beneficial for pest and weed control and it also increases the number of natural enemies (Pumariño et al., 2015).

According to global meta-analysis by Barral et al. (2015), agroecosystem restoration, such as agroforestry, can increase total biodiversity nearly 70%. Agroforestry practices increase biodiversity by providing more habitats for wildlife in agricultural lands, and acting as ecological corridors which help animals, pollen and seeds to move between different habitats (Gassner & Dobie, 2022; Jose, 2009) and by enhancing the species diversity in farmlands by increasing the variety of tree species in the croplands (Nair, 2011). In addition, agroforestry plays a role in biodiversity conservation. Increasing the number of trees in the croplands helps to reduce the negative impacts of land use change in the area when natural habitats like forests are taken into agricultural use (Jose, 2009). Moreover, more protected natural areas are less likely to be taken under agricultural use when agroforestry starts to get more common and begins to provide bigger yields for smallholders (Nair, 2011).

2.1.3 Social and economic benefits

Agroforestry provides social and financial benefits for smallholders by increasing farms' profitability. Having trees and crops and/or livestock in the land unit means that smallholders get a double benefit from the cropland: yields from crops and other products from trees. This helps smallholders to diversify their livelihood since it enables smallholders to yield multiple products from the same area along with the annual crops (Aryal et al., 2019). Smallholders might supply products like timber, fruits and firewood for their own use or for sell which helps to improve households' income (Charles et al., 2013). Variety of products increases smallholders' income security and food security since all the yields from the field are not lost if yields from one crop are ruined for some reason. In addition, by providing their own timber, firewood and fruits, smallholders save time and money since they do not have to spend them to get those products from somewhere else (Charles et al., 2013).

These social and economic benefits which agroforestry provides help to increase communities' resilience towards changing natural or climatic circumstances (Aryal et al., 2019). Due to agroforestry systems' abilities to improve farm production, ecosystem services and household income, agroforestry systems are less vulnerable and more resilient to any shocks and stresses than conventional agriculture systems (Charles et al., 2013). Since agroforestry increases smallholders' resilience to the impacts of these unnormal natural and climatic circumstances by providing fruits for sale and for farmers own consumption, it is possible for smallholders to get at least some income and food even though annual yields are ruined by extreme weather events (Quandt et al., 2017). Fruits and selling wood products are one of the main coping strategies for smallholders during unusual climate conditions (Charles et al., 2013). Trees also protect crops from the direct sunshine and the consequences of extreme weather events such as landslides and flooding (Lin, 2011; Quandt et al., 2017) which has impact on maintaining food production.

2.1.4 Challenges in adopting agroforestry practices

Despite its benefits, different economic, environmental and cultural factors can make agroforestry seem unappealing for farmers and can effect on smallholders' willingness to adopt agroforestry (Charles et al., 2013). Agroforestry is a long-term investment, which provides long-term benefits. Monoculture can provide profitable outputs in a year but for agroforestry, it can take even more than 4–7 years to get any profit (Do et al., 2020). Many smallholders may not have enough capital to invest in agroforestry simultaneously since it takes time to get the money back. They might value short-term financial profits rather than longer, more risky ones (Do et al., 2020). Also, security of land tenure affects smallholders' willingness to adopt agroforestry since smallholders might not be willing to invest on agroforestry if they cannot be certain that they are the one's harvesting and getting the financial and other benefits from it in the future (Glover et al., 2013; Lawin & Tamini, 2019). In addition, lack of land might be hindering factor for smallholders to adopt agroforestry since they might not be willing to spare the little they have for agroforestry (Mbow et al., 2014). Other factors hindering smallholders' eagerness in adopting agroforestry can be political factors, the size of the farm and labor availability and also the different characteristics of smallholders' like their skills, past experience in agroforestry, motivation, education level, gender and the time they can put in the agroforestry management (Charles et al., 2013;

Glover et al., 2013; Lawin & Tamini, 2019; Lundgren & Raintree, 1983; Mbow et al., 2014). Skills, past experience and motivation are especially important since practising agroforestry requires a lot of knowledge. For example, tree managements practices used to enhance the quality of output products and selecting the most suitable tree species in the specific site require knowledge, time, and consideration (Gassner & Dobie, 2022).

2.2 Airborne laser scanning

Airborne laser scanning (ALS) is an active remote sensing technique operated from an aerial platform from where the area of interest is scanned thoroughly with short-duration laser pulses to get three-dimensional information of a target (Holopainen et al., 2013; Straub et al., 2008). It can be also referred as light detection and ranging (LiDAR). Each time the laser pulse hits the target, a new point representing the surface of the target is created. Laser pulse can have one or more returns depending on the target object: first return usually comes back from the top of the object, and last return comes back from the ground (Beraldin et al., 2010; Holopainen et al., 2013). Trees commonly produce multiple echoes as the laser beam hits the branches at different levels from the ground. As a result, point cloud is formed where each point is a representation of the exact location where the laser beam has hit the surface. Data produced by laser scanners is saved as a LAS file which is able to contain point clouds (ASPRS, 2011).

Laser scanner defines the exact position of each point based on the time it takes for the laser beam to travel between the sensor and the target (Beraldin et al., 2010; Suárez et al., 2005). To accurately define the return time and distance to the target, the exact location and position of the laser scanner, given by onboard Global Navigation Satellite System (GNSS) and Inertial Measurement Unit (IMU) measurements, need to be defined (Beraldin et al., 2010; Pfeifer & Briese, 2007). Return time of the laser beam can be converted to the distance using the speed of light (Vauhkonen et al., 2014). The distance can be then converted to x-, y- and z-coordinates (Holopainen et al., 2013). Multiple points with x- and y-coordinates for height and z-coordinate for elevation and their arrangement in space can be used to form three-dimensional point clouds, which are three-dimensional representations of the scanned surface (Eitel et al., 2016; Vauhkonen et al., 2014).

Raster products such as digital terrain models (DTM), digital surface models (DSM) and canopy height models (CHM) produced from the point clouds are representations of ALS data in two-dimensional format (Holopainen et al., 2013; Marinelli et al., 2018). Generating these raster products starts by classifying point clouds into last and first return points: last returns representing bare ground and first returns representing the highest parts of the target surface (Ben-Arie et al., 2009). Missing values between the points are calculated by interpolation and thus a continuous surface representing the points' elevation above sea level can be created. DTM, based on only last return points, is a representation of the Earth's bare terrain while DSM, based on only first return points, is a representation of the highest elevation of Earth's surface including objects such as buildings and vegetation (Hyyppä et al., 2003a; Straub et al., 2008). CHM can be produced by subtracting DTM from DSM to get a representation of the height of the canopy and vegetation in the study area (Ben-Arie et al., 2009; Hyyppä et al., 2006). All three raster products are illustrated in Figure 2 where their differences are visible. Other metrics, such as canopy attributes, can also be generated from ALS point clouds for further analysis.

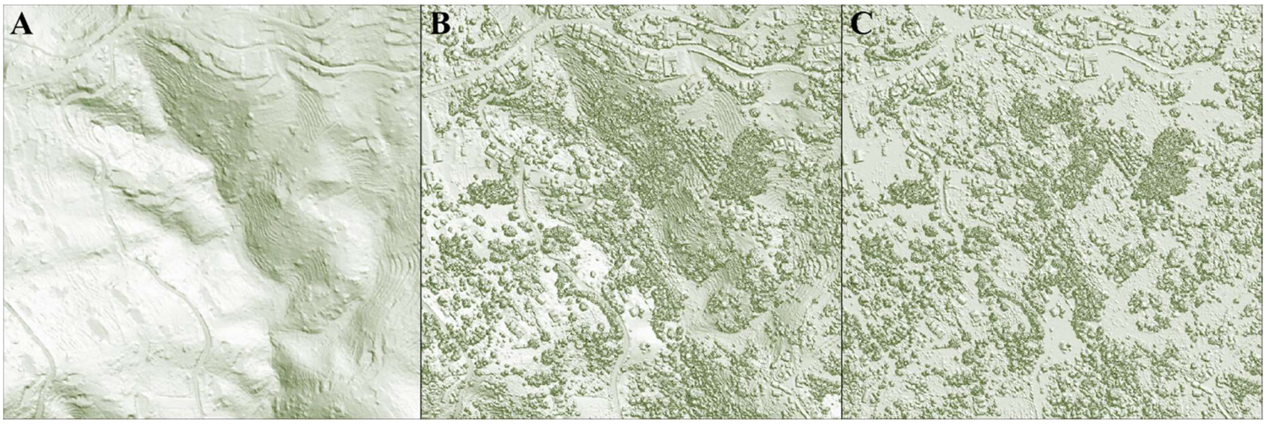

Figure 2. (a) Digital terrain model, (b) digital surface model and (c) canopy height model from Taita Hills.

Even though ALS is a beneficial tool used to study forests, canopy structures and terrain beneath them, it has few flaws, which might cause inaccuracies on final ALS products and hence need to be taken into account while analysing those. Firstly, inaccuracies occur especially while estimating the tree heights, which has been addressed profoundly by Suárez et al. (2005). According to them, most common cause for inaccuracies is laser beam missing the highest top of the canopy, which causes the underestimation of tree heights and tree height changes (Hyyppä et al., 2003b). Lower point density tends to underestimate tree heights more than higher point density (Zhao et al., 2018). Secondly, inaccuracies might occur in areas where dense vegetation or the complexity of terrain might effect on the quality of DTM, which then could have an effect on the quality of CHM (Beraldin et al., 2010; Hyyppä et al., 2003a). Increasing the point density increases the chances of laser pulse to hit the ground and beam back to laser scanner through dense vegetation, which leads to more detailed end products. In addition, terrains with high complexity require higher point density to achieve accurate representations of terrain. Different parameters such as number of pulses transmitted in time, scan angle, flight altitude and the speed of the airborne platform all have an impact on point density (Suárez et al., 2005). Thirdly, scan angle itself has effects on the quality of DTM as well and different scan angles are required depending on the study area. In areas with flat, simple terrain scan angle can be high, however, in urban areas or regions with dense vegetation, scan angle should be smaller (Beraldin et al., 2010). Fourthly, ALS products will always have small errors caused by interpolating and generalizing point clouds (Suárez et al., 2005). They are never absolute representations of reality. Lastly, any errors in the calibration of GNSS, IMU and the scanner might cause inaccuracies in the final products (Beraldin et al., 2010).

2.3 ALS in change detection of tree cover

Change detection is a process where changes in the landscape in a specific time range are observed using data sets from at least two different time points (Singh, 1989). Both laser scanning data and remote sensing images can be used in change detection studies. 2D images have traditionally been used change detection analyses but the use of laser scanning data have been increasing as it can solve some limits and errors usually faced in 2D image-based analyses (Okyay et al., 2019; Qin et al., 2016). 2D images give information only on the uppermost layer of the canopy but laser scanning makes it possible to study the vertical structures of forests and trees and ground beneath them (Marinelli et al., 2018). Whether to use laser scanning or optical images depends on the study subject but they can also be combined to have advantages from both of the methods (Zolkos et al., 2013).

Laser scanning based change detection studies can be applied in different fields across Earth sciences (Okyay et al., 2019). Depending on the study subject and the aim of the study, timescale of the change detection study can vary remarkably. Multitemporal change detection study has a time span more than a month but the time span of hypertemporal change is only a month or less (Eitel et al., 2016). Thus, the time scale of change detection study can vary from days to even several decades.

Liu et al. (2021) mention two different approaches how multitemporal comparison can be executed based on three-dimensional point clouds. In model-based comparison, point clouds are first converted into raster models such as DTM, DSM or CHM. Changes are detected by comparing possible changes in raster models from different times. The other approach is point-based comparison. In this approach changes are detected by calculating distances between points in different laser scanning data sets (Liu et al., 2021). This study utilizes model-based comparison for example with CHM from different times as it is used especially in the change detection of canopy structure and biomass (Okyay et al., 2019).

Regardless of having multiple advantages in change detection studies focusing on above ground biomass (AGB) and forest structure, ALS based change detection studies can also have some limitations or errors due to their multitemporal nature. Since ALS data is a representation of canopies in a particular time point, tree canopies can be at a different positions in different scanning times due to strong winds, which can especially affect the position of the tallest trees (Yu et al., 2006). Hence, ALS data sets might not be exactly comparable at different time points. Moreover, some errors in detecting tree growth can be caused when taller trees are cut down by revealing shorter ones previously hidden under the canopy which have not been shown in ALS data from the first time point (Yu et al., 2006). In addition, technological advancements might cause different ALS data sets not being comparable with each other since different laser scanning parameters have been used, and sensor types have been changing and getting better over time (Riofrío et al., 2022; St-Onge & Vepakomma, 2004). Differences in flight parameters can cause all kinds of biases which should be considered while examining the results (Senécal et al., 2018).

The field of studies where ALS can be applied in multitemporal research is diverse. It can be used to gather information of several kinds of terrestrial phenomena, varying from snow and ice studies to geology (Okyay et al., 2019). As stated before, it can be also applied to study changes in AGB and vegetation structures. ALS is widely used in the change detection of forest vegetation since possibilities to apply ALS data and change detection to study forest structure and growth are versatile. St-Onge & Vepakomma (2004) have applied multitemporal ALS data to detect forest gaps and assessing growth in natural forests. ALS was found to be useful method to map canopy gaps in forest landscapes. Zhao et al. (2018) studied the utility of multitemporal LiDAR to monitor for example tree growth changes based on four ALS data sets from four different years and field data from two different time points. ALS and field data sets were combined to have individual tree and landscape level knowledge of different forest parameter changes. They proved that tree heights were more underestimated with lower point densities.

Schnell et al. (2015) have noted that not many studies are focusing on applying active remote sensing methods on monitoring the changes and growth of trees outside forests. Some prior studies recently have applied ALS on detecting changes in human-modified landscapes in tropics. De Moura et al. (2020) applied multitemporal ALS to study changes in canopy height and their relationship with above-ground carbon stocks in human-modified tropical forests. They demonstrated that multitemporal ALS data can be used to monitor annual changes in carbon stocks and how the changes AGB are strongly linked to tree height changes. Nunes et al. (2021) detected forest growth in logged forest fragments in human-modified tropical landscape. Analysis was performed, for example, using top-of-canopy height in 30.0 m resolution to reduce the uncertainties caused by multitemporal ALS.

3 Study area

The Taita Hills (3°25´S, 38°20´E) are located in the northernmost part of the Eastern Arc Mountains in Taita Taveta County in south-eastern Kenya (Figure 3). They cover approximately 1000 km^2 of the whole county. As surrounded by lowlands, Taita Hills have an elevation range from 700 m a.s.l. to the highest hill Vuria reaching to 2208 m a.s.l. (Abera et al., 2023). Rainy seasons occur twice a year in the region: longer rains in March-May/June and shorter rains in October-December (Adhikari et al., 2017). Average annual rainfall is 1500 mm in the hills but it varies remarkably from year to year (Pellikka et al., 2005). Being a part of one of the biodiversity hotspots in the world, Taita Hills are known for their high biodiversity and endemicity (Myers et al., 2000). There are endemic species which inhabit only single forest patches in the hills and are thus not found anywhere else outside or within Taita Hills (Burgess et al., 2007).

Farming in the Taita Hills is intensive small-scale farming (Maeda et al., 2010) and croplands are cultivated by maize, beans, cassava, peas, millet and banana (Soini, 2005). Average farm size is 0.4 ha in the highlands of Taita Hills (County Government of Taita Taveta, 2018). Terraces are typically used in agriculture as they enable farming even in the steep slopes (Figure 4). Even tough trees on farms were rare in the 1950s (Pellikka et al., 2013), nowadays agroforestry is a common farming practice in the hills and people have shown positive attitudes towards tree planting (Githiru et al., 2011). Typical small-scale farming with trees on cropland is shown in Figure 5.

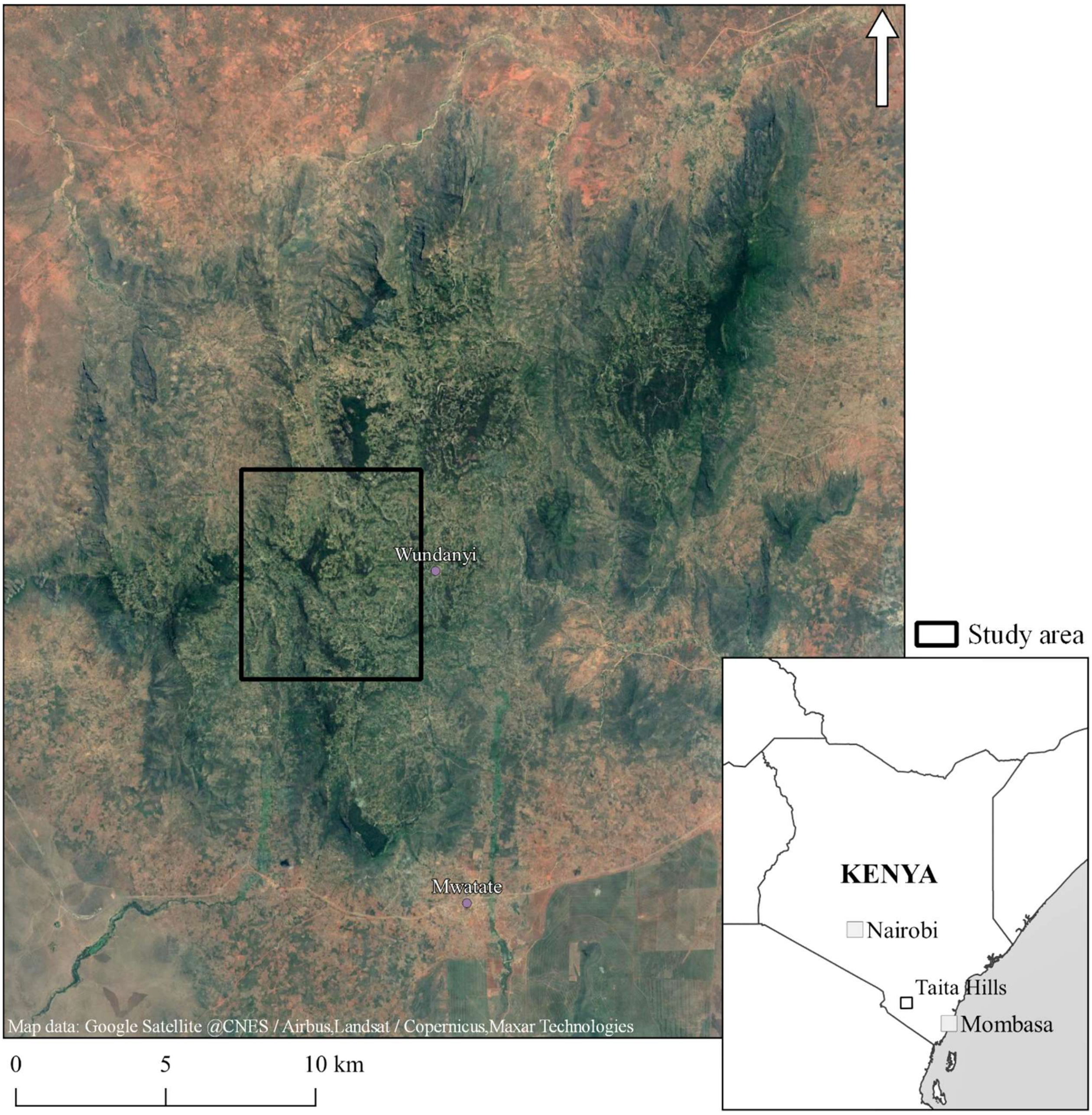

Figure 3. Geographic location of Taita Hills in south-eastern Kenya. The exact study area (6.0 km × 7.0 km) covers 42 km² of agriculture and agroforestry, montane cloud forests, exotic forest plantations and human settlements (Pellikka et al., 2013)(Google Satellite @CNES / Airbus, Landsat / Copernicus, Maxar Technologies).

Figure 4. Agroforestry landscape in terraced hills in Taita Hills (Elli-Nora Kaarto, 2022).

Figure 5. Trees on cropland in Taita Hills (Elli-Nora Kaarto, 2022).

According to survey by Soini (2005), most important tree species used in the croplands in highlands of Taita Hills are silky oak (*Grevillea robusta)*, but also mango (*Mangifera indica*) and avocado (*Persea americana)* are typical, which are used to yield fruits for sale. Black wattle (*Acacia mearnsii)* is also common tree species in the areas outside forest especially in the higher altitudes (Piiroinen et al., 2018). Silky oak, along with Mexican cedar (*Cupressus lusitanica*), eucalyptus (*Eucalyptus ssp*.) and acacia (*Acacia spp.*) are used to get timber and firewood for farmers own use but also for sale (Soini, 2005). Different tree species are also used for other than economic benefits. For example, silky oak is used to add organic matter in soil, acacia to fix nitrogen, avocado to improve soil and eucalyptus and mango to control erosion and act as a windbreak (Charles et al., 2013).

Regardless of the fact that people in Taita Hills have said to have positive attitudes towards indigenous tree species (Githiru et al., 2011), common tree species used in agroforestry in Taita Hills are exotic, and thus invasive and threats to biodiversity (K.W. Thijs et al., 2013). Avocado, mango, silky oak, black wattle, Mexican cedar and eucalyptus are all exotic species and thus not native to Taita Hills (K.W. Thijs et al., 2013). Exotic tree species are popular trees in croplands for their great agroforestry potential: they are fast-growing, they fix nitrogen in the soil and they produce large fruits for sell (Gassner & Dobie, 2022; Koen W. Thijs et al., 2015). Despite their great agroforestry potential, exotic tree species are also problematic as they spread rapidly in the surrounding areas taking place from the indigenous tree species (Gassner & Dobie, 2022). Eucalyptus trees are especially problematic for their high demand for water which leads to drying up the water sources used by other plants around them (County Government of Taita Taveta, 2018).

Rapid population growth and climate change have caused problems in Taita Hills for both people and nature. Population growth in Taita Taveta county, agricultural expansion and the scarcity of suitable land for agriculture have led to serious land use changes such as deforestation, soil erosion and landscape fragmentation as more forests have been taken under agricultural use (Adhikari et al., 2020; Maeda et al., 2010; Pellikka et al., 2005, 2013). However, slight increases in the forest area have been detected in recent decades (Pellikka et al., 2018). Effects of climate change, unpredictable weather patterns and rains, rising temperatures, and people's inability to prepare and adapt to them have led to decreased crop yields and food insecurity (County Government of Taita Taveta, 2018).

4 Data and methods

4.1 Field data

This study is based on two different field data sets acquired in Taita Hills in 2013 and 2022. In 2013, 100 biomass inventory plots were randomly sampled within 100 ha clusters around the Taita Hills. The size of each plot was 0.1 ha, and all plots were circular with the radius of 17.84 m. For this study, I selected 28 plots with the land use of agroforestry or other agriculture from the 100 plots based on the assumed change that may have happened in the plot. Change was examined by comparing ALS data from 2014/15 to recent Bing very high resolution satellite images from the area (NextGIS, n.d.). Field data plots were also chosen from five different clusters to have sample data from different parts of the study area (Figure 6). Recent field data was gathered in Taita Hills during the spring 2022. The chosen 24 plots were visited during 23–27 January and the last four on 12 May.

In 2022, field data was aimed to be gathered following the similar procedure as in 2013. Chosen plots were located using the coordinates of plot centers. Plot centers were not marked during the first field work, which made it difficult to locate the centers for the second time. In 2013, the diameter at breast height (DBH, ca. 1.3 m above the ground), crown diameter (CD, outer perimeter of the whole crown) and height were measured for all the trees with DBH ≥ 10 cm. The position of each measured tree was estimated based on their direction and distance from the plot center. Tree species was identified for each measured tree. In 2022, trees still present in the 28 chosen plots were measured again, missing trees from the previous data set were marked and measurements were taken for new trees with DBH ≥ 10 cm. If the tree had more than one trunk with DBH ≥ 10 cm, trunks were measured separately. Measurements were done using the measuring tape, compass, and laser range finder for the tree height in 2022. In 2013, tree height measurements were acquired by a clinometer (Suunto). All plots visited in 2022 were photographed, their current land use was described, and aspect of the plot was estimated.

In total, measurements were taken for 285 trees in 2013 and 2022. Most common measured tree species were silky oak and black wattle as indicated in Figure 7. During the field work, 217 trees were measured in 2013 and 185 trees were measured in 2022. All trees were not measured twice but 108 trees had measurements from both years. Missing measurements were usually caused by unpractical or impossible field work conditions. Descriptive statistics for the field plots are given in Table 1.

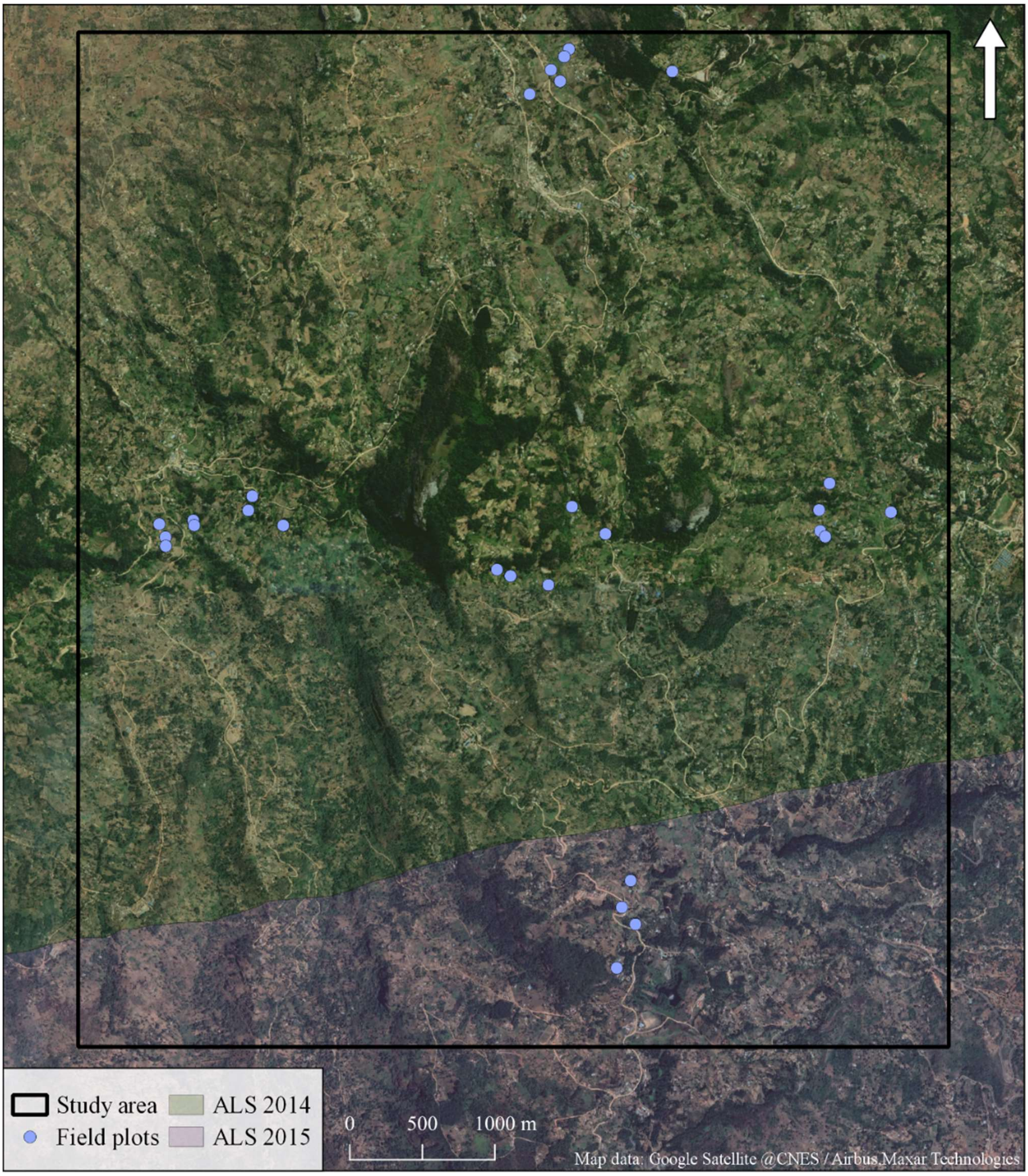

Figure 6. Locations of field data plots within the study area (Google Satellite @CNES / Airbus, Maxar Technologies).

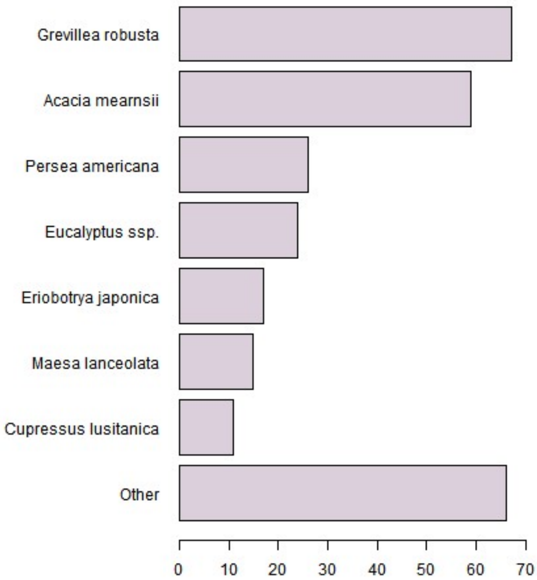

Figure 7. Most common tree species in field data plots in 2013 and 2022.

Table 1. Descriptive statistics for field data plots (n=28).

	No. of trees		**Mean DBH (cm)**		**Mean height (m)**		**Mean CD (m)**	
	2013	*2022*	*2013*	*2022*	*2013*	*2022*	*2013*	*2022*
Min.	1	0	10	14.0	6	5.8	3.5	3.9
Max.	20	13	40.8	65.3	18.2	27.0	8.7	11
Mean	7.6	6.6	23.7	28.6	11.1	13.9	6.3	6.6
SD	4.9	4.0	7.3	10.7	3.5	5.1	1.2	1.9

4.2 ALS data

ALS data used in the study were collected in 2014/15 and 2022. Data from 2014/15 has been combined from two different data sets from different years (Figure 6). All ALS data have been acquired at the same time of the year using the same sensor Leica ALS60. ALS data have different flight altitudes and mean pulse densities. Further characteristics for ALS data are given in Table 2. Both ALS data were already pre-processed by the data vendor (Ramani Geosystems) and data sets were then delivered as georeferenced point clouds in UTM/WGS84 coordinate system with ellipsoidal heights. Since both data sets covered a wider area in the hills, only tiles covering the study area were chosen for analyses.

Table 2. Characteristics for ALS data.

	ALS 2014/15	ALS 2022
Date of acquisition	Feb 2014 and Feb 2015	Feb/Mar 2022
Sensor	Leica ALS60	Leica ALS60
Mean flight altitude above ground (m)	1460	800
Pulse rate (kHz)	58	99
Scan rate (Hz)	66	59
Scan angle (degrees)	± 16	± 20
Mean pulse density (per m^2)	4.55	6.49
Mean return density (per m^2)	5.06	7.01

4.3 Processing ALS data

4.3.1 Point classification and raster products

Workflow for data processing is illustrated in Figure 8. The processing of LiDAR point clouds was carried out using LAStools in the command prompt. LAStools is designed to process large point cloud data sets with a great variety of command line tools (rapidlasso GmbH, n.d.). Exactly same procedure was followed, and same batches were utilized to process both ALS data sets to ensure that they are comparable. This ensures that detected changes are actual changes in the landscape and not only caused by using different processing methods with different data sets (Riofrío et al., 2022).

Canopy height changes could be analysed with either CHMs or DSMs. For example, Hyyppä et al. (2006) compared DSMs from different times to estimate tree growth. However, comparing CHMs to estimate canopy height changes in this study is justified since then results are not affected by changes in terrain, which are likely in human-modified landscape. To get more information of canopy height changes also from other perspective, 99th percentile canopy height raster layers are also used in the analyses.

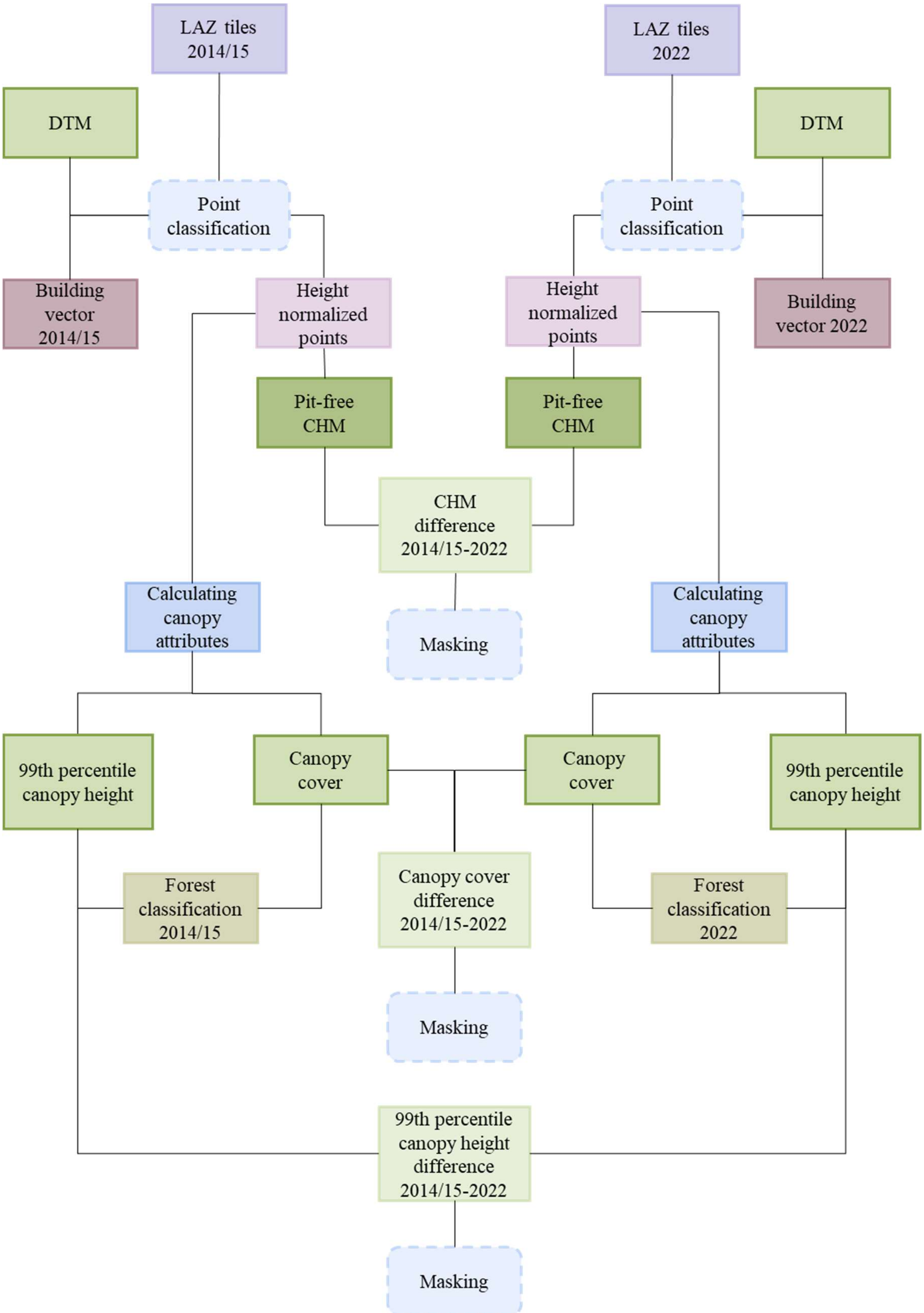

Figure 8. General workflow for airborne laser scanning data processing.

Processing of ALS data started with point classification (Figure 9) and classifying points into ground and non-ground points. Ground classification was executed for both ALS data sets separately by classifying all points into ground points using *lasground_new* tool in LAStools. Step size of 10 m ('town' option) was used to classify ground points. It was found to be most well suited for this kind of environment since the other options with smaller step size had too much noise in forests and bushy regions or had otherwise bad results for building classification later. During ground classification, noise and overage points were excluded to avoid unwanted artifacts in the raster products later. Heights were computed during classification.

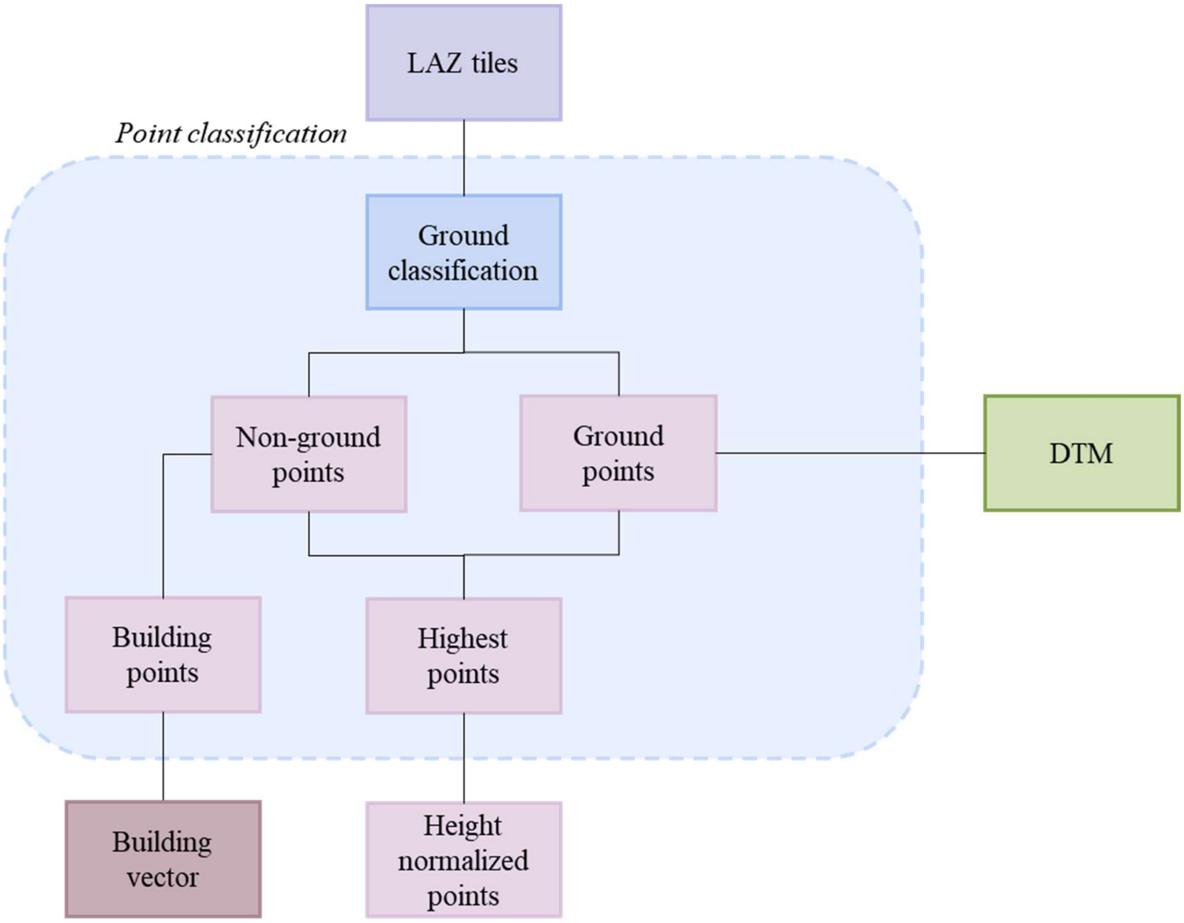

Figure 9. Detailed workflow for point classification.

In the quality assessment of the ground classification, separate DTMs were created for both years. DTM was created using *blast2dem* tool, which creates raster DTMs for each tile in the data having ground classified points as input. Ground classified points are first triangulated into a TIN and after that TIN is rasterized into a DTM. The illustrations of ground classified points and triangulated ground classified points before rasterizing are shown in Figure 10. Filter '-thin_with_grid 0.5' was used to take only one ground point per 0.5 m × 0.5 m area, which ensures that the output is appropriate for the final output resolution of 1.0 m × 1.0 m. In addition, '-use_tile_bb' parameter was used to rasterize the TIN only to the tile area. *Lasgrid* was used to grid DTM data onto a raster in a UTM/WGS84 coordinate system.

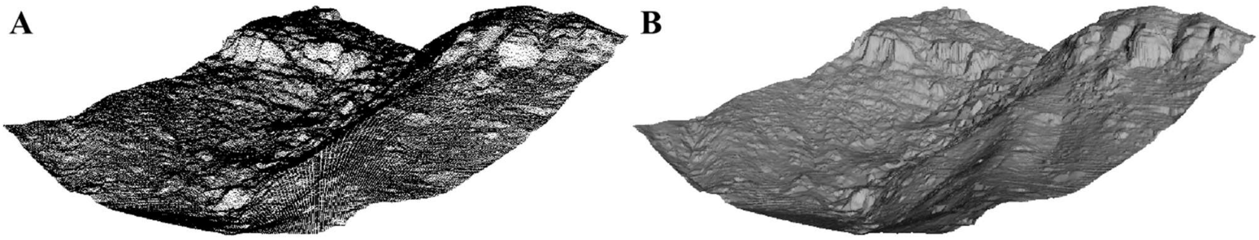

Figure 10. (a) Ground classified points and (b) triangulated ground classified points in the area of single LAZ tile.

In prior change detection studies by Nunes et al. (2021), Senécal et al. (2018) and St-Onge & Vepakomma (2004), combined DTM is used in the analyses by combining ground points from both time points to avoid errors in canopy height caused by differences in terrain. However, in this study, using separate ground points for both times was a conscious choice since it has been expected to be highly likely that there has been changes in terrain between two different years as agricultural landscape is constantly under human use. Moreover, the quality of separate DTMs were examined visually for possible errors in ground classification, for example, due to the lack of ground classified points in the areas of very dense vegetation. Both DTMs and ground classification seemed to have good quality to proceed with the processing.

After classifying ground points and excluding noise and overage points from the data, all other points classified as non-ground points were further classified into building and high vegetation points by *lasclassify*. Step size 3 was used to reduce the chances of misclassifying vegetation as buildings. Results of building classification were not as desirable as they should be to reliably remove points classified as building at this step of the processing. Thus, buildings were included in the final CHM, but they were masked out later in the processing process. Points classified as buildings were used to create vector layer for building masking. First classified points were tiled into tiles without buffers with *lastiles* tool and after that *lasboundary* tool was used to create boundary polygons for points classified as buildings. The resulted vector layer was used as a part of a building mask later during processing.

Since point classification for buildings was not perfect, the need for manually editing some buildings within field plots was noted.

CHM is generated using height-normalized LiDAR points. Height-normalizing started by creating thinned tiles with only highest points of the point cloud using *lasthin* tool. With a parameter '-subcircle' points were expanded to footprint of the laser pulses. Only the highest points of the data were considered using '-highest' parameter. Noise and overage points were excluded from computation, but buildings were still included since they were masked out from the final outputs anyway. Parameter '-step 0.5' was used to set grid cell size to 0.5 m for thinning.

Height normalization for the thinned tiles was executed with *lasheight* tool, which creates tiles with normalized heights for the CHM computation and computes the height for each point above the ground. It assumes that ground points have already been classified. Points below 0 m and above 60 m were dropped to avoid errors since height of the vegetation is expected to be positive and trees in agroforestry areas are expected to be shorter than 60 m. Taller trees might exist in forests but since forests are going to be masked out for the further analyses, 60 m threshold was set to be appropriate for the purposes of this study. The illustration of height-normalized point cloud and triangulated height-normalized points are shown in Figure 11.

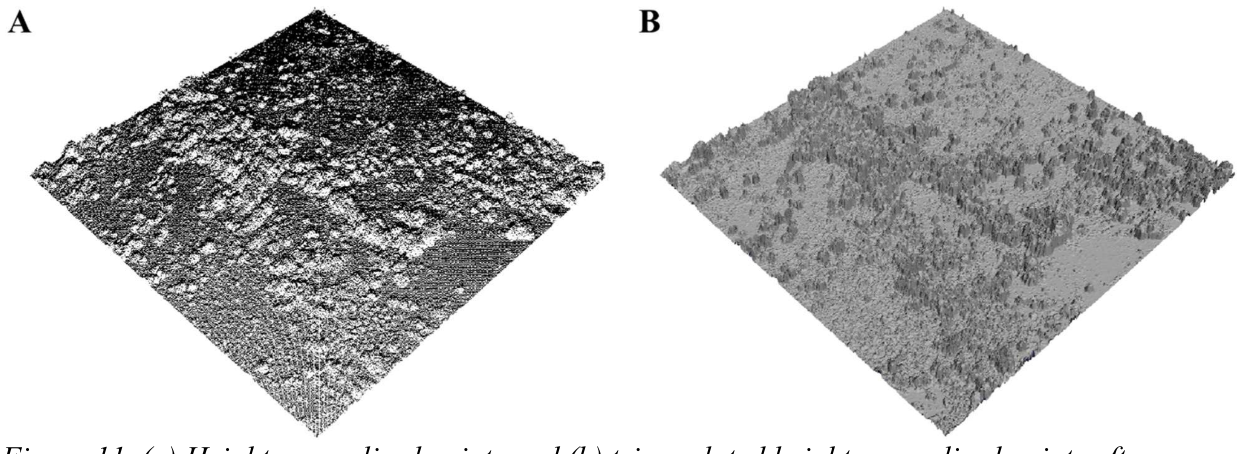

Figure 11. (a) Height-normalized points and (b) triangulated height-normalized points after triangulating in the area of single LAZ tile.

4.3.2 Creating pit-free CHM

CHM could be computed using blast2dem with similar principles as computing DTM previously but having height-normalized points as input instead of ground points. However, this way final CHM could end up having some unnecessary empty pixels, so called pits, whenever laser beam has penetrated deeply through the canopy before hitting any surface and generating first return (Khosravipour et al., 2014). Pits can reduce the quality of CHM and cause inaccuracies later in the analysing process since they have remarkably lower values than their neighboring pixels (Ben-Arie et al., 2009; Shamsoddini et al., 2013). In Figure 12a, pits can be recognized as empty pixels resulting inaccuracies also in hillshade visualization. In the visualization of pit-free CHM (Figure 12b), pits are removed and hillshade visualization is smoother. To get rid of these unnecessary pits, pit-free algorithm generated by Khosravipour et al. (2014) was applied to create pit-free CHM raster.

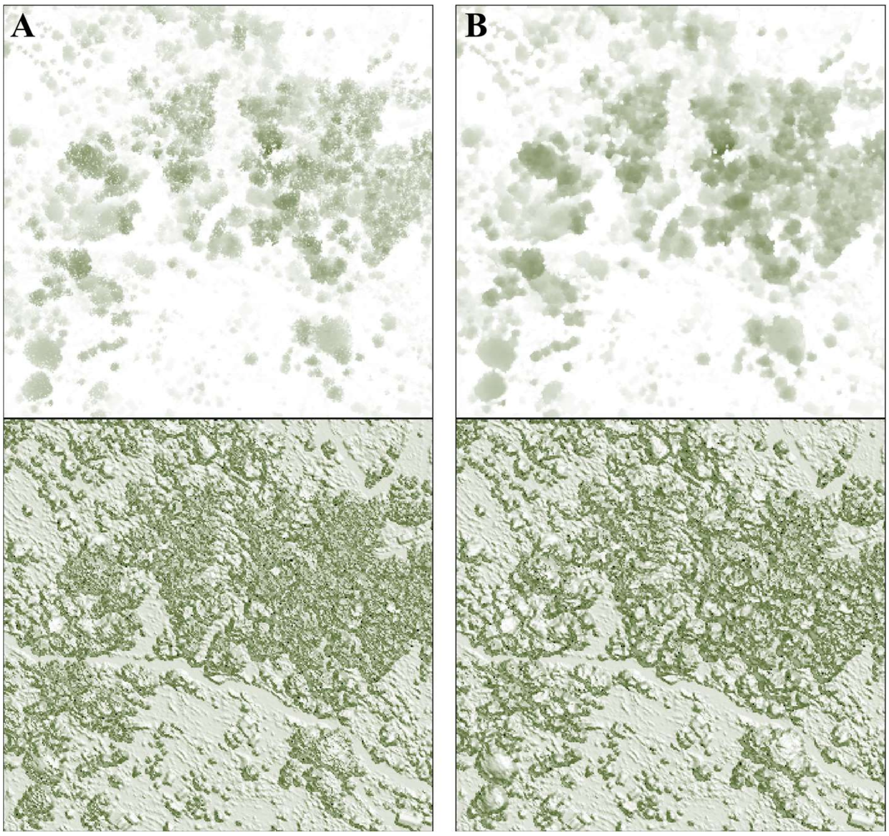

Figure 12. Comparison of (a) normal canopy height model and (b) pit-free canopy height model from Taita Hills. Figures above have standard visualization and figures below have hillshade visualization.

The processing of pit-free CHM is illustrated in Figure 13. Actual processing for pit-free CHM was carried out using blast2dem tool. Using the height normalized points, partial CHMs are calculated separately with different height thresholds: 0, 2, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 and 55 m. First height threshold (0 m) considers all first returns creating a normal CHM. The height threshold of 2 m considers all first returns above 2 m, the height threshold of 5 m considers all first returns above 5 m and so forth. Parameter '-use_tile_bb' is used to rasterize the TIN only to the tile area. All thresholds are gone through similarly to have 13 partial CHMs, which are finally combined and grid onto a raster in a UTM/WGS84 coordinate system with the output resolution of 1.0 m × 1.0 m. When combined, for the location of each raster cell the maximum value of all partial CHMs is chosen as output value to have CHM without pits (Khosravipour et al., 2014). The descriptive statistics for both processed CHM are described in Table 3. Mean height in 2022 is higher which might be caused by higher point density in 2022. The illustration of pit-free CHM from 2022 is shown in Figure 14a.

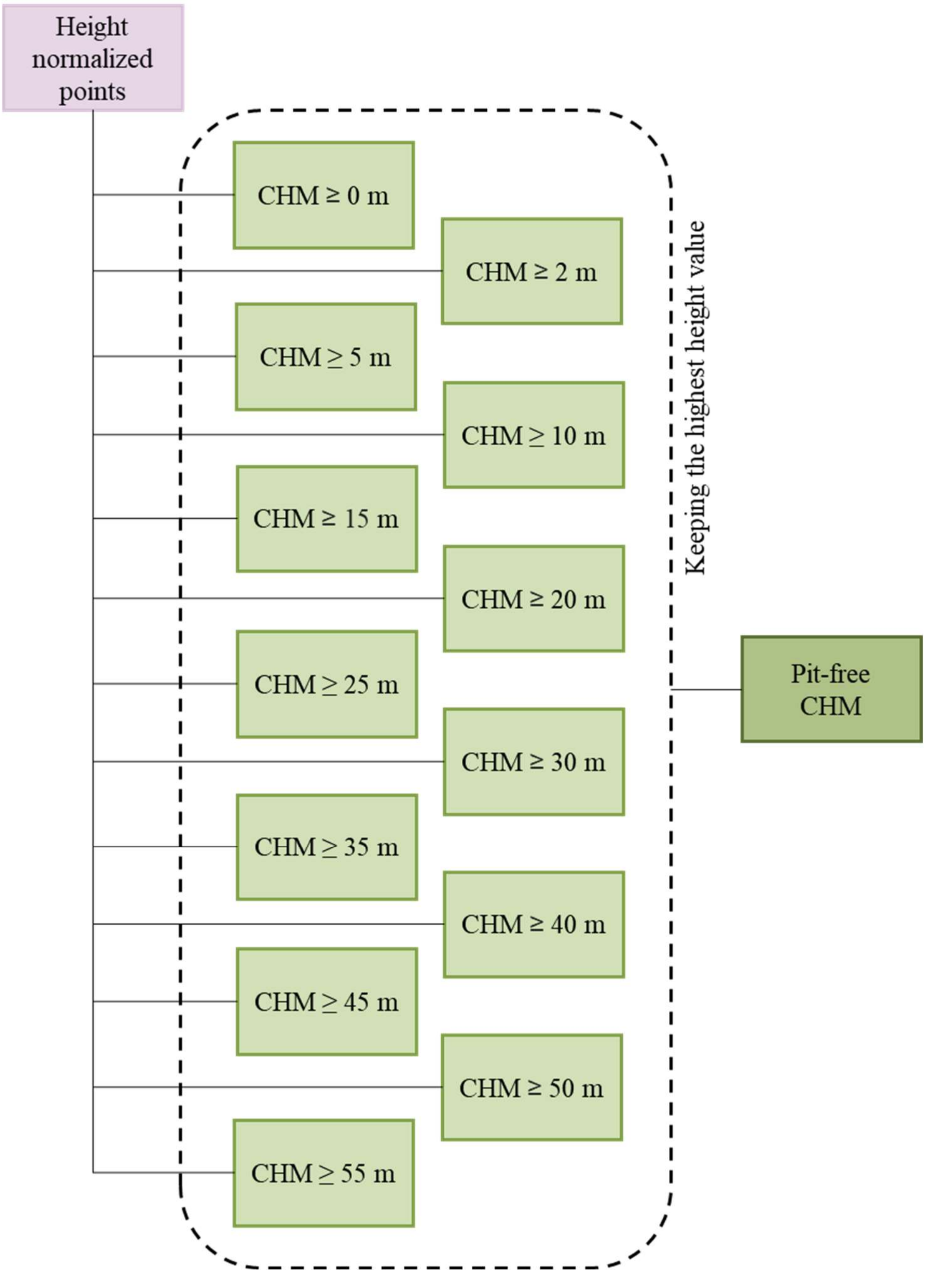

Figure 13. The structure for generating pit-free canopy height model modified from Khosravipour et al. (2014).

4.3.3 Calculating canopy attributes

Canopy metrics such as canopy cover and maximum heights were calculated using *lascanopy* tool in LAStools. Here, resolution was set to 10.0 m × 10.0 m. Only points above the height threshold of 2.0 m were considered. Maximum of all heights above height threshold for each 10.0 m × 10.0 m grid cell was computed using 99th percentile height. When the highest 1% of points within each cell is dropped out from the calculations, it helps to avoid errors for example caused by some random branches reaching the cell from neighboring cells. The output for maximum height within each grid cell is in meters. Canopy cover for each 10.0 m × 10.0 m cell is computed as the number of first returns above the height threshold of 2.0 m divided by the number of all the first returns in each cell. The output of canopy cover calculations is reported as a percentage. Illustrations of the processed 99th percentile height and canopy cover raster layers from 2022 are shown in Figure 14b and 14c and descriptive statistics for corresponding layers are described in Table 3. As with CHM, mean height for 99th percentile height was higher in 2022.

Table 3. Descriptive statistics for processed CHM, 99th percentile canopy height and canopy cover raster layers.

	CHM (m)		**99th percentile canopy height (m)**		**Canopy cover (%)**	
	2014/15	*2022*	*2014/15*	*2022*	*2014/15*	*2022*
Min.	0	0	0	0	0	0
Max.	59.97	59.96	59.96	59.96	100	100
Mean	4.02	4.24	10.34	10.79	35.7	35.4
SD	6.57	6.86	8.27	8.54	31.5	31.2

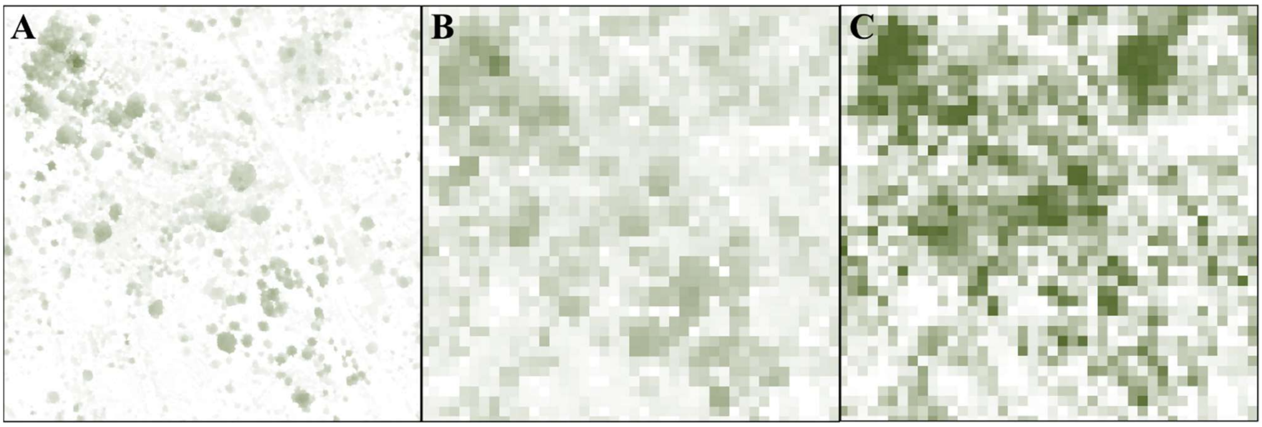

Figure 14. (a) Pit-free canopy height model, (b) 99^{th} percentile canopy height and (c) canopy cover raster layers from 2022.

4.4 Change detection

4.4.1 Landscape level analysis

Change detection analysis was carried out using QGIS 3.10 A Coruña software (QGIS.org, 2019). The canopy height changes between 2014/15 and 2022 were calculated by subtracting 2014/15 pit-free CHM from 2022 pit-free CHM, creating a layer with CHM changes in a resolution of 1.0 m × 1.0 m. Canopy cover and 99th percentile height changes between 2014/15 and 2022 were calculated similarly but in a resolution of 10.0 m × 10.0 m. After subtraction, unnecessary objects were filtered out from raster layers. Masking out unnecessary objects was carried out similarly for all layers following the workflow in Figure 15, but mask layers were converted to suitable resolution (1.0 m or 10.0 m) depending on the resolution of input raster layer.

Masking out unnecessary objects started with masking out buildings using two building vectors from ALS processing. Since the building classification was not perfect, few buildings were manually digitized concentrating on the regions covered by the study plots based on the aerial imagery acquired simultaneously with ALS data. In total 10 missing buildings were manually digitized. Building vectors from 2014/15 and 2022 and the ones manually digitized, were rasterized to 1.0 m resolution. All three building layers were merged, reclassified, and masked out from the CHM, 99^{th} percentile height and canopy cover raster layers. Masking was executed using Raster calculator -tool.

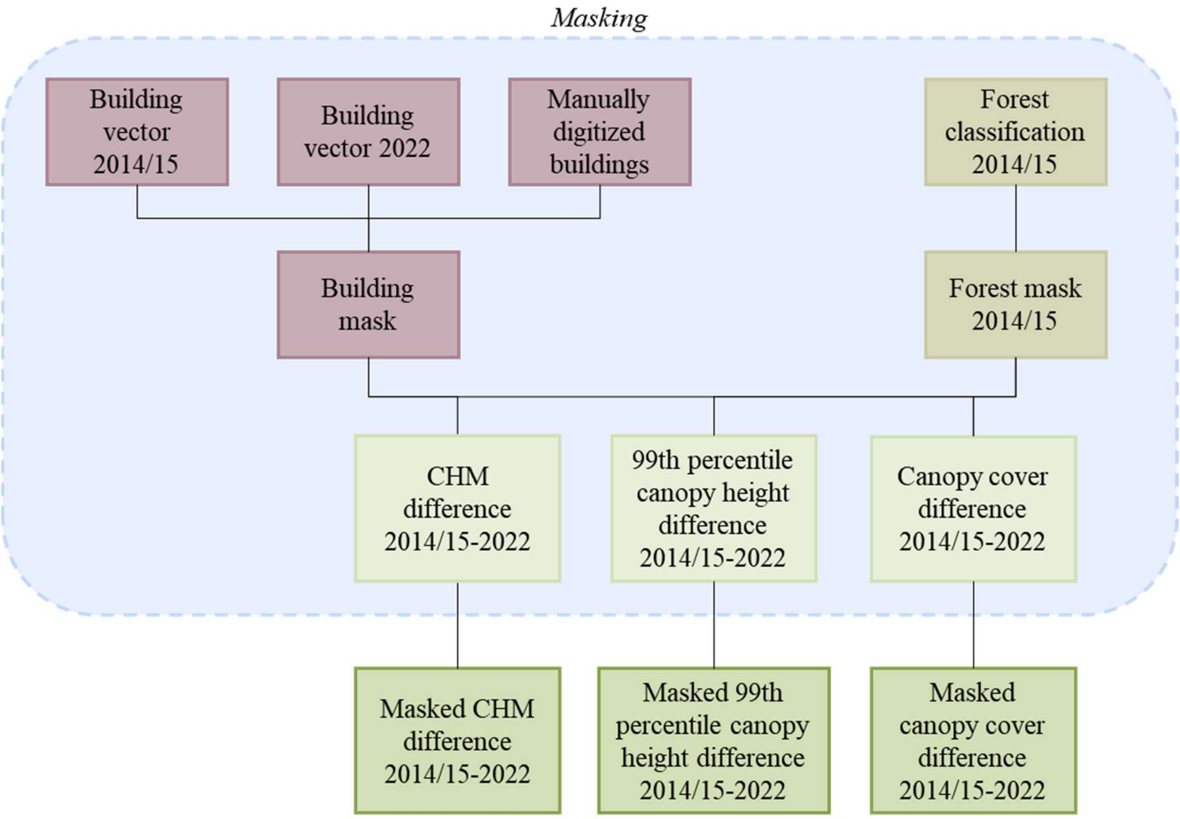

Figure 15. Workflow for masking CHM, 99th percentile canopy height and canopy cover raster layers.

To be able to focus on changes in agroforestry and trees outside forest, forest was masked out from the study area. Forests are commonly defined by minimum tree height, canopy cover and the size of the forest patch. However, the definition of forest depends on the used source. According to FAO (2020), land areas ≥ 0.5 ha, with tree height ≥ 5.0 m and canopy cover ≥10% are defined as forests. This definition does not include land under agricultural use. Kenya's national forest definition differs slightly from the FAO's definition. According to them, land areas ≥ 0.5 ha with tree height ≥ 2.0 m and canopy cover ≥ 15% are defined as forests (Government of Kenya, 2020). However, almost half of the agricultural land has at least 10% tree cover globally (Zomer et al., 2016). Also, Taita Hills is expected to have higher canopy cover in the croplands. Thus, 10% or 15% canopy cover is too low to identify denser montane and exotic forests stands in Taita Hills. According to Government of Kenya (2020), closed canopy forests in Kenya have canopy cover more than 65%, which was more suitable criteria for canopy cover in forest classification. The height threshold in Kenya is set quite low to 2.0 m to cover also the driest forest types in Kenya. Thus, 5.0 m height was found to be more suitable for forest classification in Taita Hills. The minimum size of the forest patch was set to 0.5 ha, which allows small forest stands to remain in the farmland.

According to both forest definitions by FAO (2020) and Government of Kenya (2020), trees do not need to be over 2.0 m or 5.0 m or canopy cover does not need to be more than defined. Trees and canopy cover can be smaller than given values, but they need to be able to reach those thresholds in the given conditions. However, since the possibility to reach the values is difficult to estimate using ALS, forests are classified based on the tree heights and canopy cover at the time.

Classification of areas outside forest was following the rules in Straub et al. (2008): areas not fulfilling the criteria set for the forests were classified as non-forest and are thus on the focus further in the study. Forest classification was first done to 2014/15 data since areas having forest vegetation in 2014/15 needed to be excluded from the change detection analysis. For further analysis, 2014/15 forests were excluded from CHMs from both years. Forests were classified in QGIS using Raster calculator -tool and canopy attributes processed previously in LAStools. Only 10.0 m × 10.0 m raster cells reaching the given canopy height and canopy cover thresholds were chosen. Forests patches < 0.5 hectares were removed from the classified forest patches producing forest mask layer in 10.0 m × 10.0 m resolution, but it was also converted into 1.0 m × 1.0 m resolution. Forest mask layer was reclassified and masked out from the CHM, 99th percentile height and canopy cover raster layers. Masking was executed using Raster calculator -tool.

In the analysis of differences in canopy height and canopy cover were further analysed, negative values expressed decrease in tree heights in meters and loss of tree cover in percent, while positive values expressed increase in tree heights in meters and tree cover in percent. In both cases, if the difference between two study points was 0, no change has occurred in the specific spot. In the change detection of canopy height from CHM, even the smallest changes between ± 2.0 m were included to be able to analyse the smallest changes in canopies but also new trees and other woody perennials < 2.0 m in croplands.

Areas with tree loss and canopy height increase were further identified with CHM and 99th percentile canopy height difference between 2014/15 and 2022. Threshold was set to -5.0 m to identify tree loss and to 2.0 m to identify canopy height increase. Related to a national goal for reaching 10% tree cover by 2020 (Republic of Kenya, 2019), the change in the area having 10% canopy cover during 2014/15–2022 was analysed. The sizes of the area in which there is < 10% canopy cover in 2014/15 but reaching

≥ 10% canopy cover in 2022, and vice versa, the area of having ≥ 10% canopy cover in 2014/15 but having < 10% canopy cover in 2022 were also analysed.

Change in the forest area during the study period was also further analysed. As forests were already classified for 2014/15, forests were classified also for 2022, to make be able to compare the forest area in different time steps.

4.4.2 Plot level analysis and validation

Field measurements from 28 field plots had two purposes. First, they were used to get plot level information of canopy height and canopy cover changes, and secondly, they were also utilized for the validation of ALS-based analyses. Firstly, validation of ALS-based analyses was carried out by matching the trees in both field and ALS data sets. Aim of the tree matching was to find out how much trees have grown based on the field data and ALS data, and if the tree height estimates derived from ALS data differ from field-based estimates. Tree matching was executed by detecting the trees from the CHMs of 2014/15 and 2022 based on their location and tree heights from both time points were taken manually by extracting the highest value of each tree segment (Hyyppä et al., 2003b). If it was not possible to recognize a tree in both CHMs with a high accuracy, height measurements were not registered. Vegetation in CHM was sometimes too dense to recognize some trees with high accuracy, because shorter trees were hidden by the canopy of taller trees, or the location of the tree was incorrect In total, 72 trees were identified in both CHMs and were used further.

As a result of tree matching, there were four height measurements for each 72 trees: field-measured tree heights from 2013 and 2022 and ALS-measured tree heights from 2014/15 and 2022. Height difference between the two time points was calculated by subtracting previous ALS/field data from the recent ALS/field data and the height difference was used as increase in the tree height, meaning growth. Growth rate per year was calculated for tree heights and their changes. For ALS-derived heights, growth rate was calculated between 2014 and 2022, since most of the field plots had ALS data from 2014. Tree growth in the study plots was also analysed by examining the DBH and CD values measured in the field. DBH was measured from 120 tree trunks in both years, while 97 trees had CD measurements in 2013 and 2022. Measurements from both years were compared to each other. Spearman correlation coefficient was used analyse correlations between measured tree attributes from different years or from different data set.

Secondly, validation of ALS-based analyses was carried out by calculating average absolute deviations (AAD) separately for both field-measured and ALS-measured tree height changes. AAD of tree height changes was calculated using the following equation:

$$\frac{1}{n}\sum_{i=1}^{n}|x_i - m| = \frac{|x_1 - m| + |x_2 - m| + \cdots + |x_n - m|}{n}$$

Thirdly, validation of ALS-based analyses was also carried out by comparing changes in the number of trees in plots to canopy height from CHM and canopy cover measurements derived from ALS data. The difference in the number of trees in a plot were simply calculated by subtracting the number of trees identified in 2013 from the number of trees identified in 2022 in purpose to find out if the number of measured trees in the study plots have been increasing, decreasing or if the number of trees has remained the same. If the tree was clearly dead in 2022 even though it was standing, it was not counted as an existing tree. Validation was proceeded by calculating the mean canopy height and canopy cover changes within each plot and comparing results on changes in number of trees in each plot. For each circular vector polygons representing the boundaries of field plots, Zonal statistics -tool in QGIS was used to calculate the mean of each pixel within the polygon. Statistics were calculated for CHM and canopy cover changes, but in canopy height analyses, only pixels with canopy height change ≤ -2 m and ≥ 2 m were considered. Height changes between ± 2 m were excluded so that the smallest height changes would be left out.

5 Results

5.1 Changes at landscape level

Canopy height change was observed by detecting change between two CHMs from 2014/15 and 2022. Canopy height change was also observed using 99th percentile canopy height in comparison to CHM change. Respectively, change in canopy cover was observed by detecting change between two ALS derived canopy cover raster layers from corresponding years. Change in canopy structure was first analysed at landscape level.

Figures 16, 17 and 18 illustrate canopy height and canopy cover changes in the study area. Areas with distinct decrease and increase in canopy structure can be easily identified in all the figures. In addition, areas with distinct canopy height decrease and increase in Figures 16 and 17 can also be identified as canopy cover decrease and increase in Figure 18. In some areas, canopy height and canopy cover has been clearly increasing more rapidly than in other areas. In addition to areas with distinct change in canopy structure, small negative and positive change seem to be quite evenly widespread in the whole study area.

Based on 99th percentile canopy height change in Figure 17, canopies seem to have grown faster compared to CHM change in Figure 16. In addition, 99th percentile canopy height decrease seems to be more vivid compared to CHM change. Based on visual interpretations, it seems like there are more areas with positive canopy height change than areas with negative change. However, it seems like there are as many areas with positive canopy cover change as areas with negative change (Figure 18).

Results for canopy height and canopy cover change were similar. At landscape level, both positive and negative change in the analysed metrics were detected. However, both canopy height and canopy cover seemed to have had more positive than negative change during the study period. Visual comparison of how canopy height and canopy cover changes are regionally distributed in the study area reveals that both changes have similar trend in the specific places.

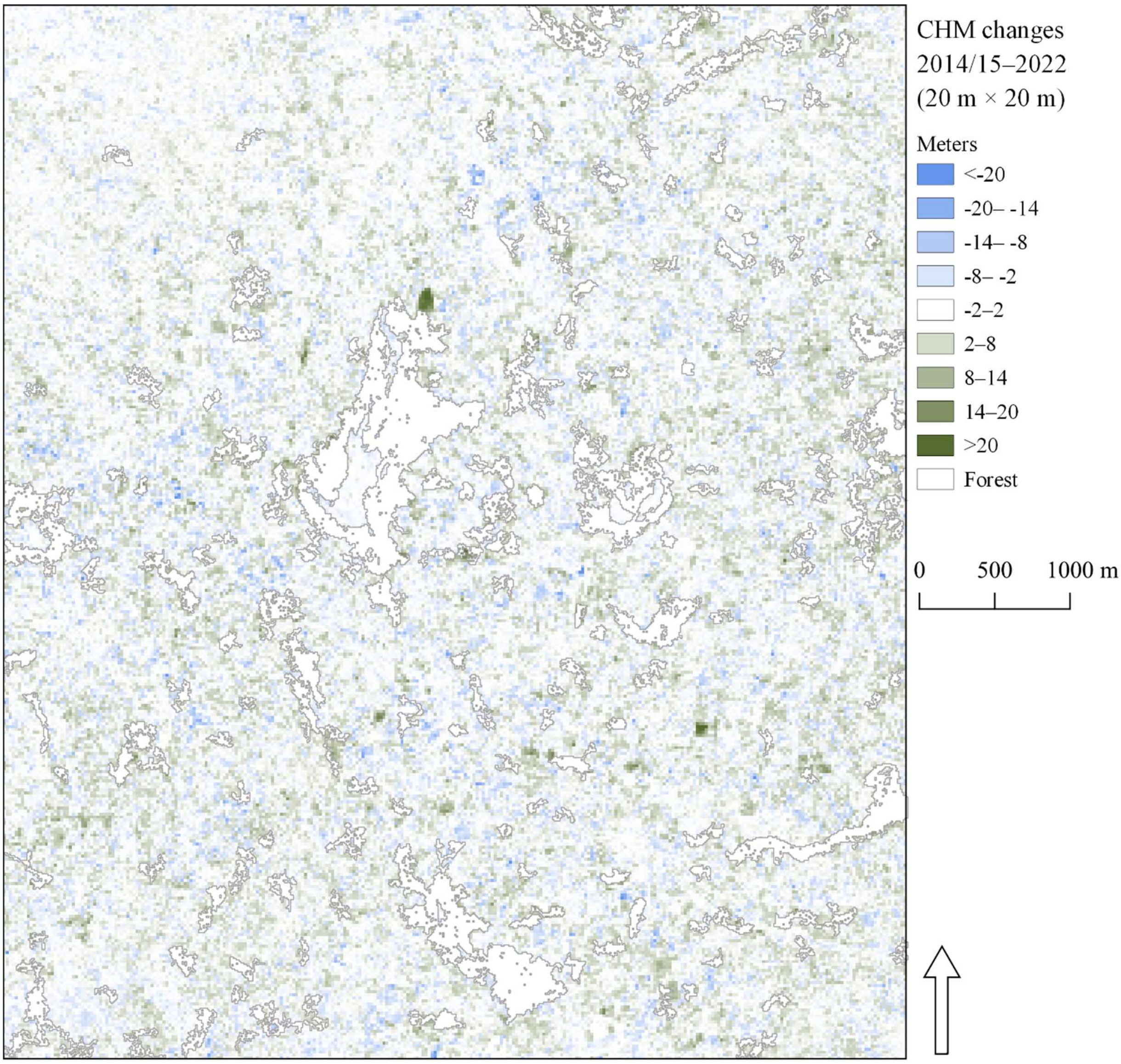

Figure 16. Changes in canopy heights in the Taita Hills, Kenya between 2014/15 and 2022 estimated from airborne laser scanning data.

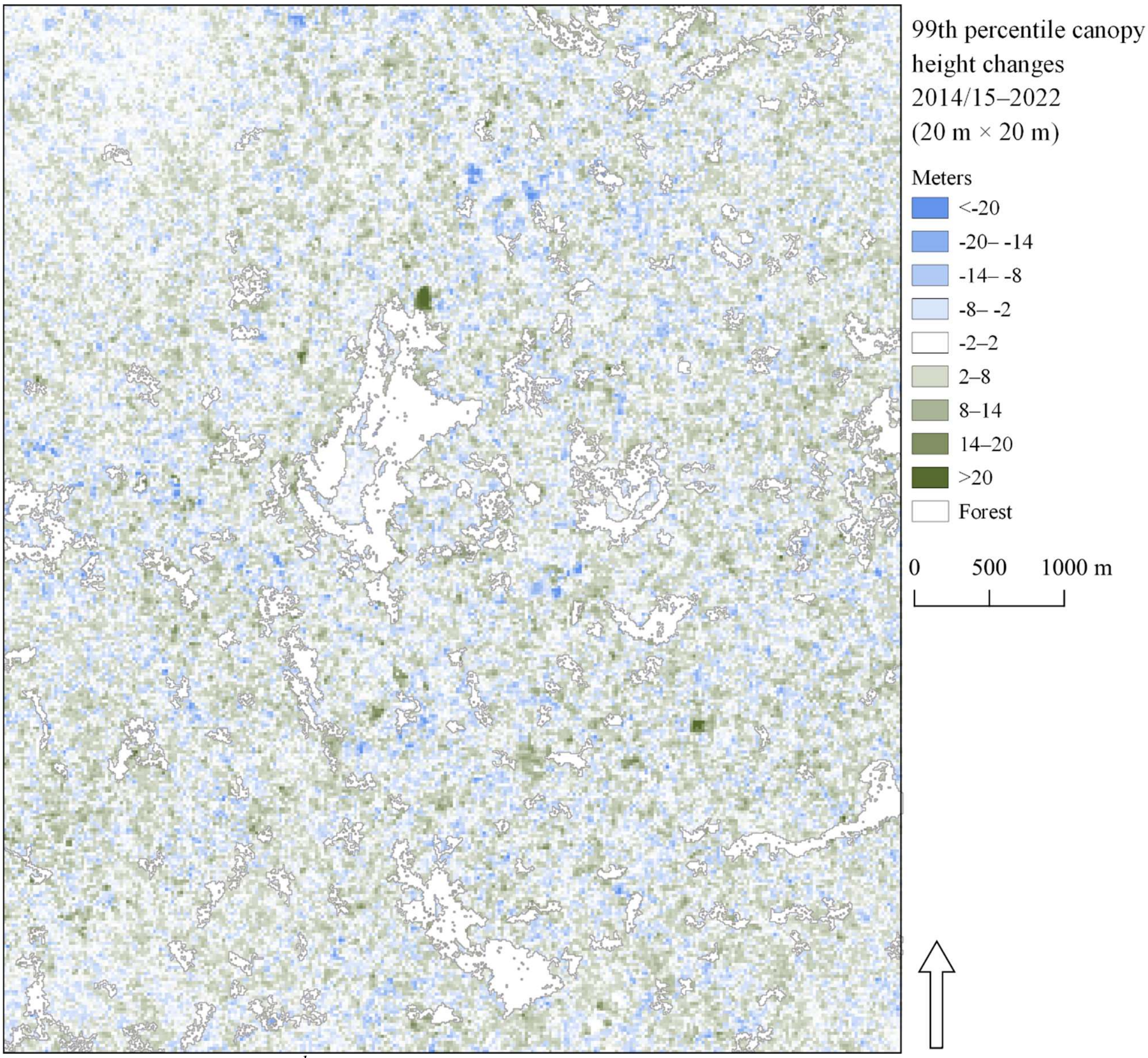

Figure 17. Changes in 99th percentile canopy heights in the Taita Hills, Kenya between 2014/15 and 2022 estimated from airborne laser scanning data.

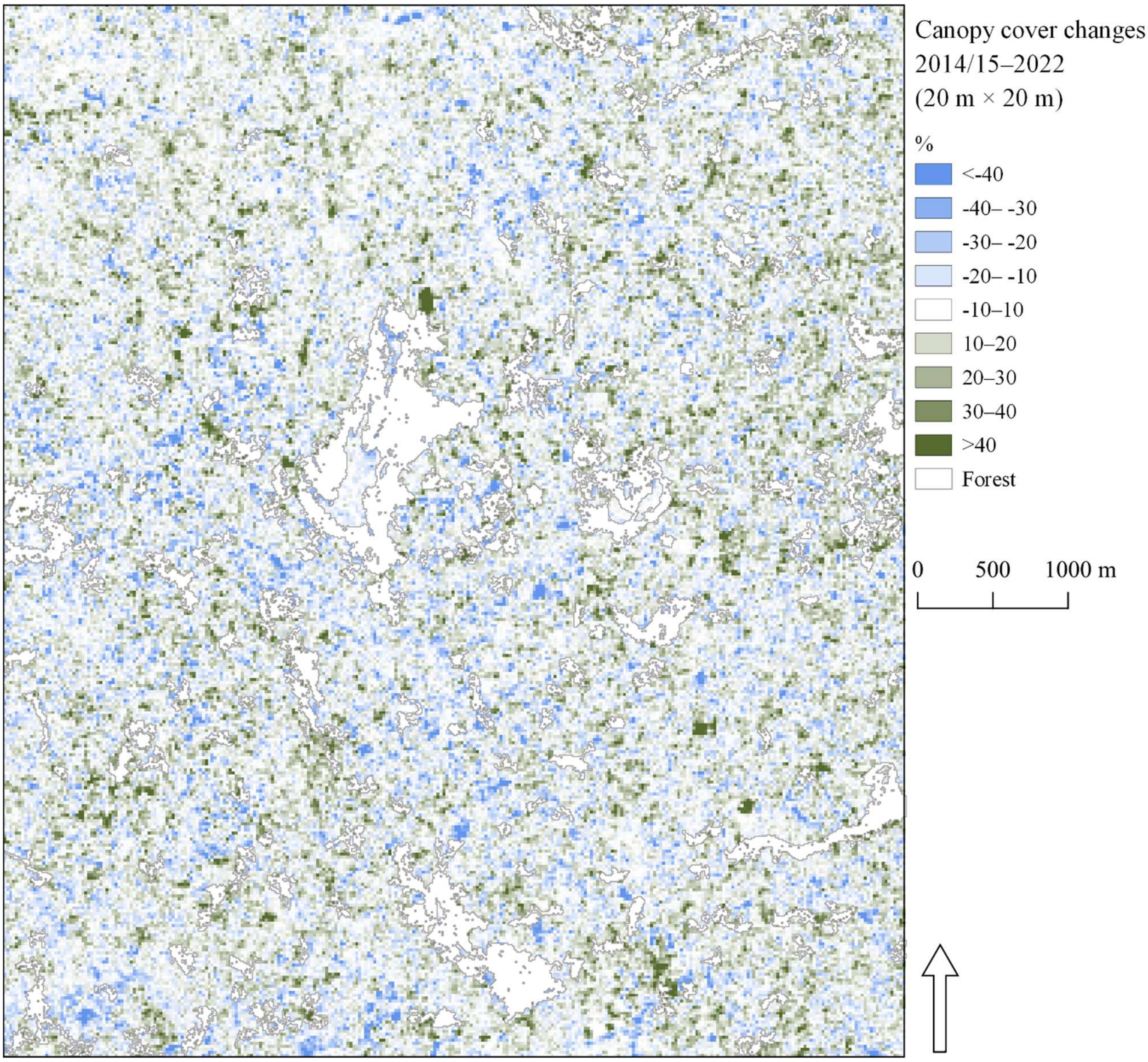

Figure 18. Changes in canopy cover in the Taita Hills, Kenya between 2014/15 and 2022 estimated from airborne laser scanning data.

Figures 19a-c illustrate the distribution of raster cells indicating canopy height and canopy cover changes. Based on CHM and 99th percentile canopy height changes, canopy height seemed to have both positive and negative change at landscape level between 2014/15 and 2022. In both cases, distribution of raster cells indicating canopy height change is normally distributed; neither positive nor negative change is clearly more emphasized than other. However, it seems like positive change is slightly more common than negative change. As shown in the Figure 19a, majority of raster cells indicating canopy height change seem to have values between -1–1 indicating that in most places it is not possible to identify rarely any change in the height of the vegetation. These observations are supported by statistics presented in Table 4. Mean for CHM change is 0.30 m and mean for 99th percentile canopy height change is 0.47 m which suggests that trees have grown more based on 99th percentile canopy height.

Results for canopy cover change are highly similar compared to results for canopy height change. Figure 19c illustrates that both positive and negative change have occurred. Distribution of raster cells indicating canopy cover change is also normally distributed. High majority of raster cells indicating canopy cover change seem to have small values near 0 which indicates that in most places it is not possible to identify much change in the canopy cover in the study area. Statistics in table 4 support these observations.

Table 4. Summaries of canopy height and canopy cover changes. Sample of 100000 cells were used in the estimating statistics, which is 0.2% of all cells in canopy height and 23.8% of all cells in canopy cover.

	Min.	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
CHM change (m)	-43.54	-0.53	0.00	0.30	1.13	45.36
99th percentile canopy height change (m)	-50.07	-1.75	0.54	0.47	3.21	48.91
Canopy cover change (%)	-100	-8.6	0.5	1.25	12.6	100

Increase in canopy height was examined by detecting the area with ≥ 2.0 m increase. Decrease in canopy height was examined by detecting area with ≤ -5.0 m, which also indicated tree loss. Based on CHM change, the area with the canopy height increase ≥ 2.0 m was 740 ha, which is 19.9% of the total area outside of forest. However, 7% of the area outside forest experienced tree loss during the same time frame as the area of 261 ha had canopy height decrease ≤ -5.0 m. Corresponding results for 99th percentile canopy height changes indicate that 1312 ha of the area had canopy height increase ≥ 2.0 m being 37.2% of the total area. Tree loss was detected covering an area of 450 ha which was 12.1% of the total area.

Slightly different approach was used in detecting canopy cover change. The area with ≥ 10% canopy cover increased from 2508 ha to 2532 ha, which was an increase from 67.4% to 68.0% with ≥ 10% canopy cover in the area outside forest. The area with < 10% canopy cover decreased from 1215 ha to 1190 ha meaning a decrease from 32.6% to 32.0% in the area outside forest. The area with < 10% canopy cover in 2014/15 but ≥ 10% canopy cover in 2022 was 445 ha being 12.0% of the area outside forest. Respectively, the area with ≥ 10% canopy cover in 2014/15 but < 10% canopy cover in 2022 was 421 ha being 11.3% of the area outside forest.

Figures 20a-c illustrate changes in the share of canopy height and canopy cover of the total area within specific thresholds. Canopy height based on CHM and their shares of the total area are shown in the Figure 20a. The share of canopy height of 0 m increased from 14.1% to 20.6% between 2014/15 and 2022. At the same time, the share of canopy height of 0–2.5 m decreased from 56% to 47%. Share of canopy height > 10.0 m increased from 9.0% to 10.6%. Other thresholds have not had remarkable changes during the study period.

Figure 20b illustrates 99th percentile canopy height and their shares of the total area. During 2014/15–2022, the area of canopy height of 0–2.5 m decreased from 5.3% to 4.2% and 2.5–5.0 m decreased from 18.2% to 15.6%. Canopy height of > 10.0 m increased from 38.1% to 41.7%. Distribution of 99th percentile canopy height is different to distribution of canopy height from CHM. Canopy heights are evaluated visibly taller based on 99th percentile canopy height than CHMs. In 2022, 41.7% of the area outside forest had canopy height > 10 m based on 99th percentile canopy height. Based on CHM, this area was only 10.6%.

Canopy cover thresholds and their share of the total area are shown in Figure 20c. Thresholds of 0–10% and >50% are clearly most common canopy coverages in the area. The share of canopy cover of 0–10% decreased from 22.8% to 21.6% and canopy cover of > 50% increased from 23.4% to 25.1% during 2014/15–2022. At the same time, nearly all other canopy cover thresholds have had a decrease in their share of the area.

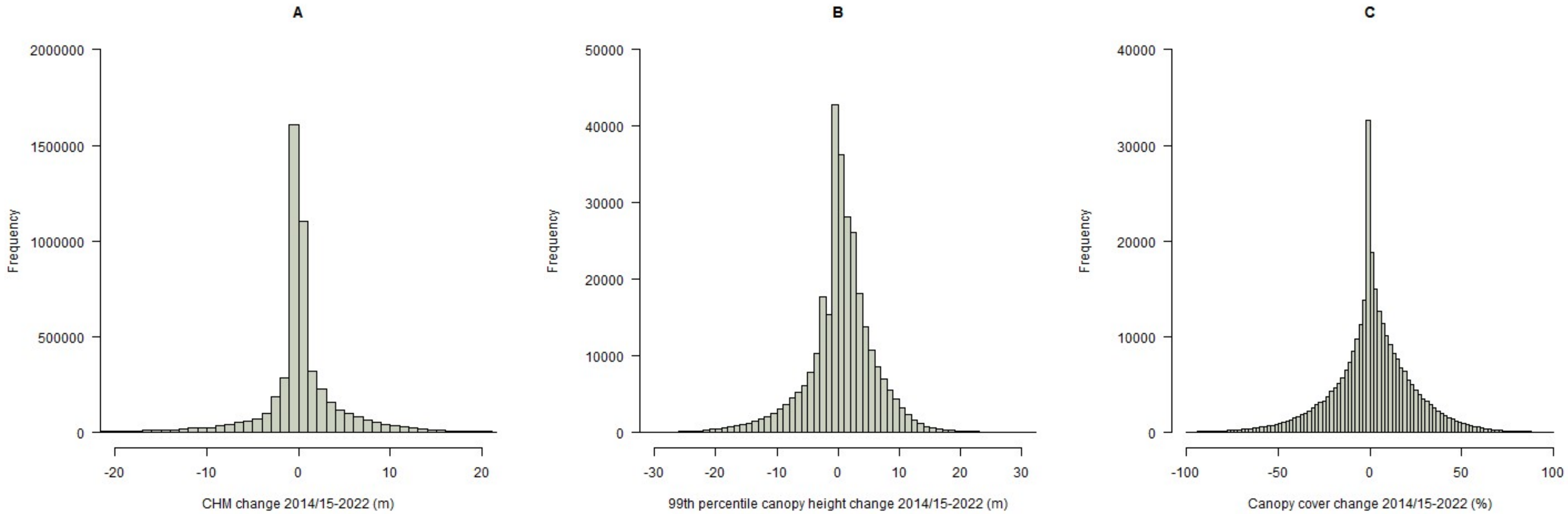

Figure 19. Histograms representing (a) CHM changes (12% of the raster cells were used), (b) 99th percentile canopy height changes (71% of the raster cells were used) and (c) canopy cover changes (71% of the raster cells were used).

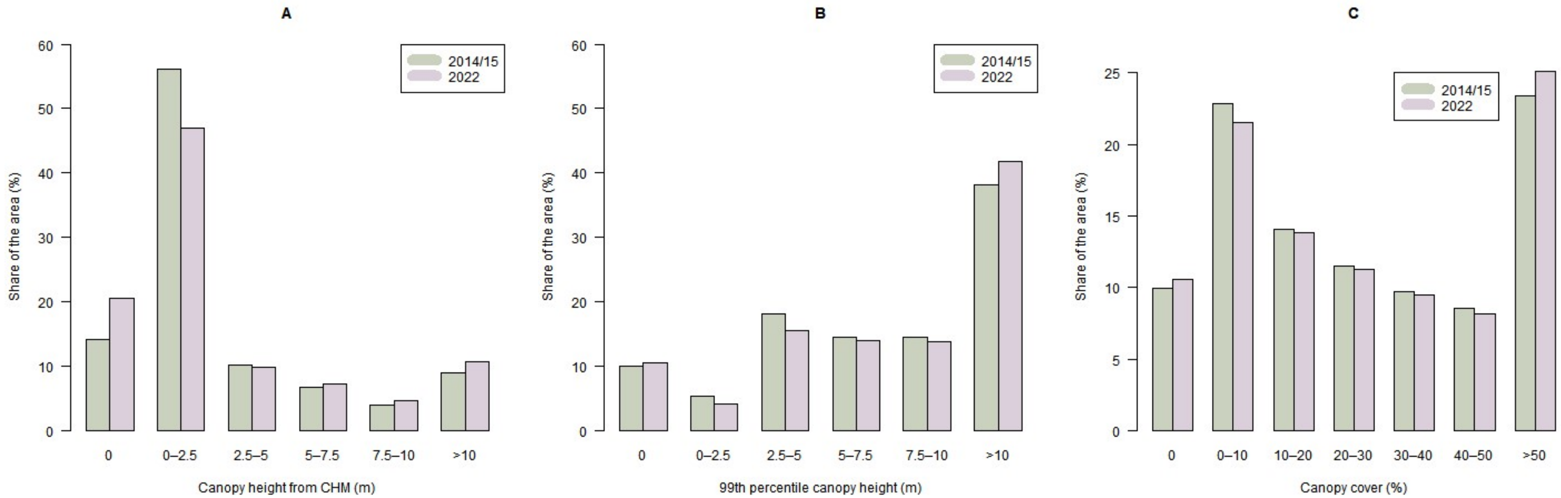

Figure 20. Changes in the share of (a) canopy height from CHM, (b) 99th percentile canopy height and (c) canopy cover of the area within specific thresholds.

Forest cover change during 2014/15–2022 is shown in Figure 21. Between 2014/15 and 2022 forest cover has decreased from 418 ha to 383 ha being a decrease of 4.4 ha/year. Some forest parcels have diminished in size and some smaller forest parcels have totally disappeared. However, some new patches of forest have appeared all around the study area.

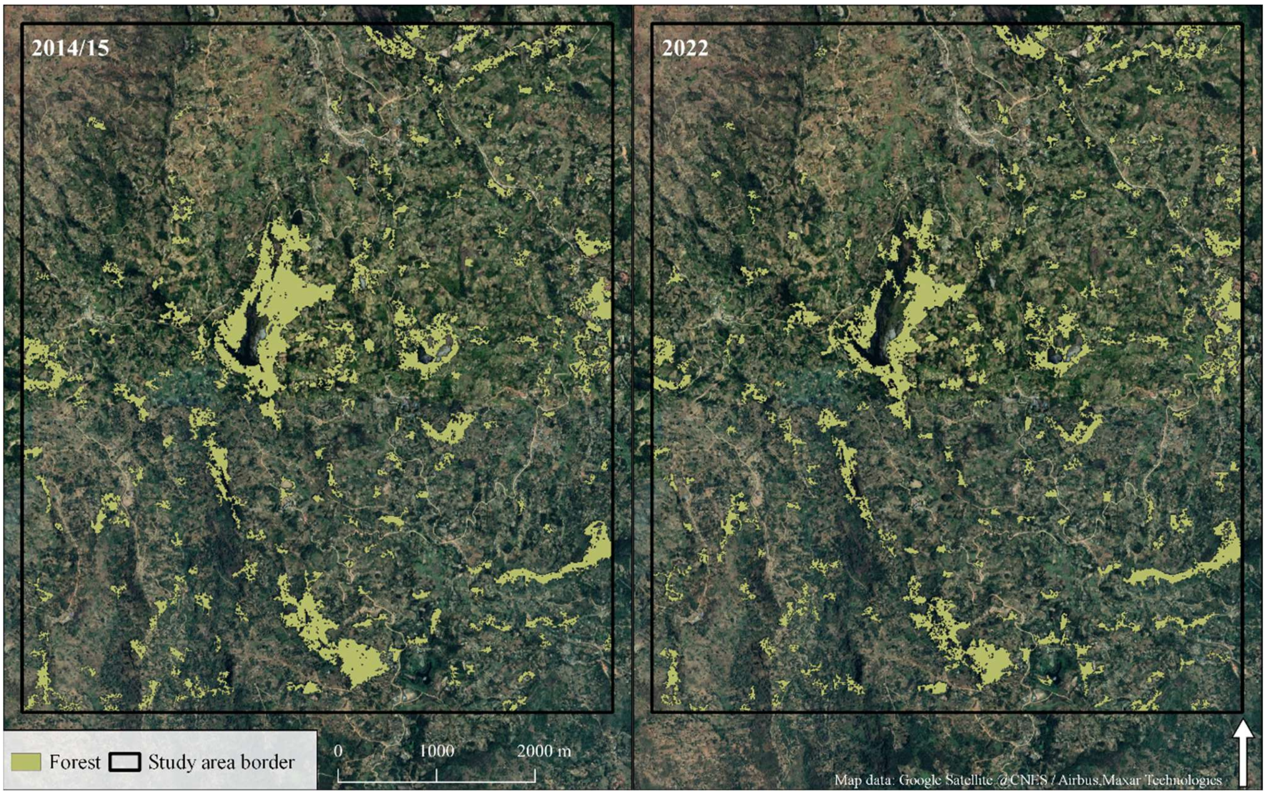

Figure 21. Forest cover change during 2014/15–2022 (Google Satellite @CNES / Airbus, Maxar Technologies).

5.2 Changes at plot level and validation of ALS-based analyses

Field-measured tree heights were used in the validation of ALS-based analyses. Validation was executed by comparing field-measured tree heights and tree height changes to ALS-derived tree height measurements (n=72). Results of validation are shown in Figure 22. When field-measured tree heights from 2013 and 2022 were compared to ALS-measured tree heights from 2022, it was found out that tree heights from corresponding year were matching well with each other (Figure 22a and 22b). Field-measured tree heights from 2013 correlated strongly ($\rho = 0.93$) with ALS-derived tree heights from 2014/15. Tree height measurements from 2022 had also strong correlation ($\rho = 0.93$). In both cases, shorter trees were matching better than taller ones. ALS-measured tree heights from 2014/15 were 0.7

m higher than field-measured heights from 2013. In 2022, ALS-measured tree heights were 0.4 m smaller than field-measured heights. Other statistics for tree height measurements are shown in Table 5.

Comparisons of field-measured tree heights from 2013 and 2022 and ALS-measured tree heights from 2014/15 and 2022 demonstrated the tree height growth during the study period (Figure 22c and 22d). Based on these comparisons, it seems like there is more variance in field-measured tree heights (ρ = 0.81) than ALS-measured ones (ρ = 0.92). Both scatterplots indicate that trees have grown during the study period. The mean field-measured tree height increased from 12.5 m to 15.6 m during 2013–2022 being an increase of 0.34 m/year. Respectively, the mean ALS-measured tree height increased from 13.2 m to 15.2 m during 2014/15–2022 being an increase of 0.25 m/year (Table 5).

Table 5. Descriptive statistics for the trees with both field-measured and ALS-measured tree heights from both time points (n=72).

	Field-measured tree heights (m)		**ALS-measured tree heights (m)**	
	2013	*2022*	*2014/15*	*2022*
Min.	4.0	3.7	4.5	3.6
1st Qu.	8.0	8.8	8.1	8.1
Median	10.0	15.4	10.9	15.2
Mean	12.5	15.6	13.2	15.2
3rd Qu.	15.3	19.9	17.8	20.2
Max.	35.0	36.2	43.3	50.3

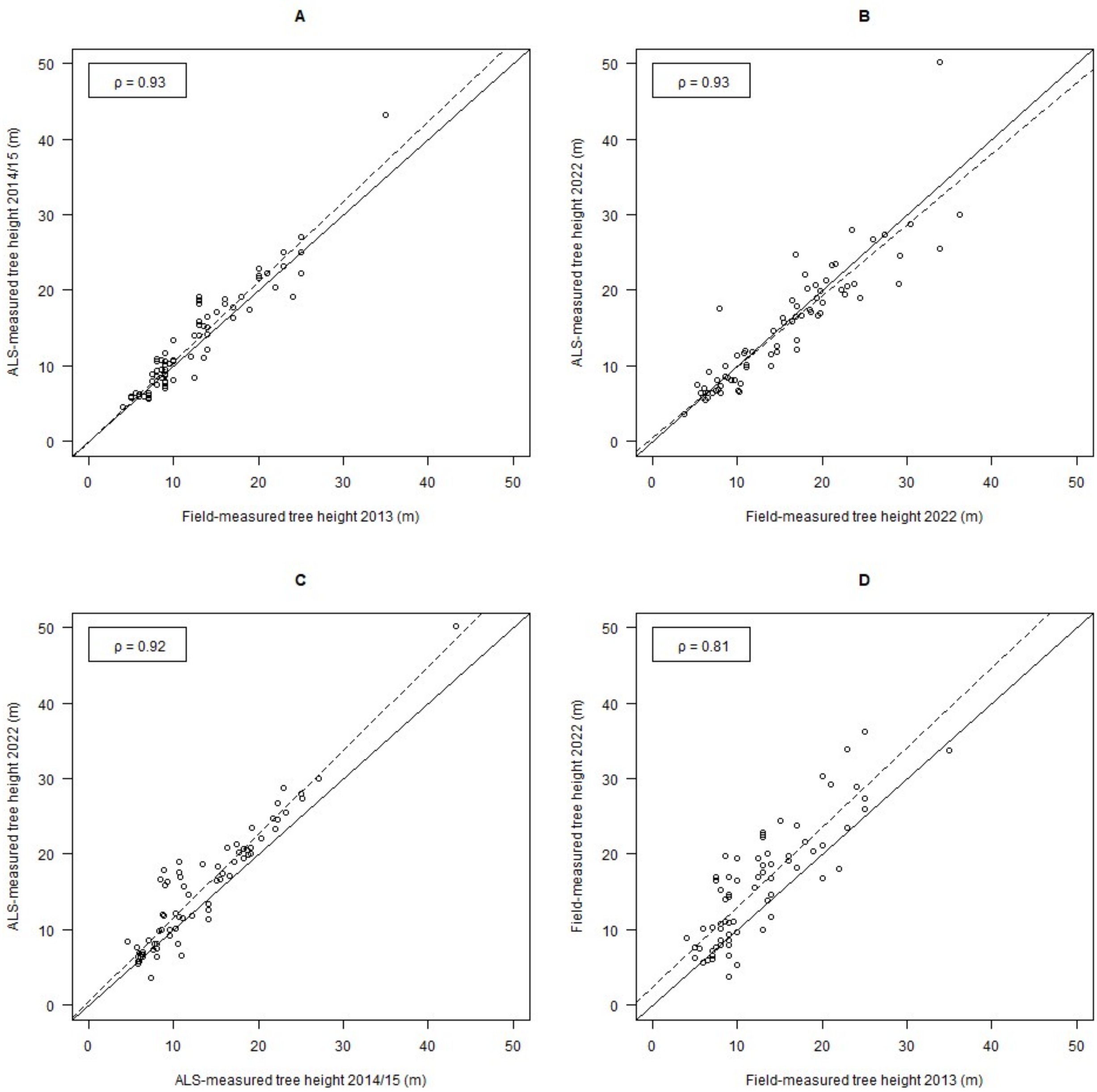

Figure 22. Comparison of field-measured and ALS-measured tree heights for (a) 2013 and 2014/15 and (b) 2022 and comparison of (c) ALS-measured tree heights between 2014/15 and 2022 and (d) field-measured tree heights between 2013 and 2022 (n=72).

The relationship between field-measured and ALS-measured tree height changes are shown in the Figure 23. Tree height changes have a moderate correlation ($\rho = 0.54$). Comparison of changes based on two different data sets in Figure 23b suggests that ALS-measured tree height changes are generally smaller than changes based on field data. Majority of trees have grown 0–3.0 m based on ALS data but based on field measurements, more trees have grown over 3.0 m. Statistics in Table 6 support these observations: for field-measured tree height mean change is 3.12 m, but for ALS-measured heights it is 1.97 m. Considering the difference in the length of study periods, field-measured change is 0.35 m/year and ALS-measured change is 0.25 m/year.

AAD for field-measured tree height changes was 3.40 m and for ALS-measured tree height changes 2.09 meters, which indicates that ALS measurements underestimate tree height changes by 1.31 m.

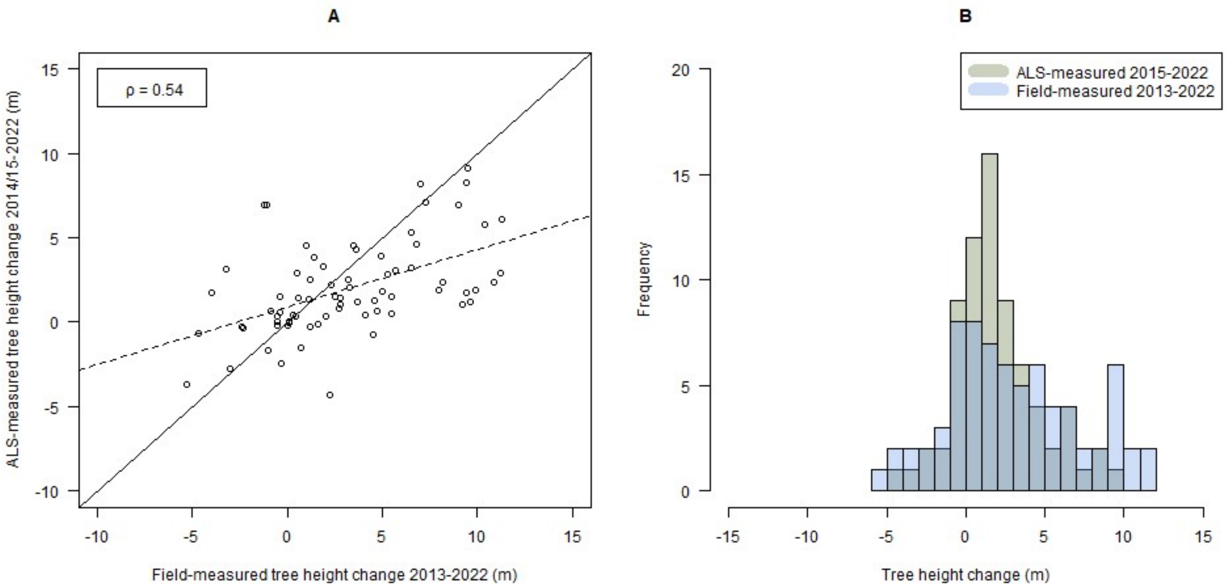

Figure 23. Comparisons of (a) field-measured tree height changes from 2013 to 2022 to ALS-measured tree height changes from 2014/15 to 2022 and (b) distributions of ALS-measured and field-measured tree height growth (n=72).

Table 6. Tree height change statistics (m).

	Min.	1st Qu	Median	Mean	3rd Qu.	Max.
Field-measured tree height change	-5.30	0.08	2.60	3.12	5.90	11.30
ALS-measured tree height change	-4.31	0.33	1.53	1.97	3.17	9.09

Comparison of field-measured DBH and DBH growth are demonstrated in Figure 24. Nearly each of the measured tree trunks have grown during 2013–2022 except for one tree trunk which had same DBH in 2013 and 2022. Average growth for DBH was 8.98 cm (Table 7) but there was a great variance in the growth rate between trees. Three separate peaks can be roughly distinguished in DBH growth (Figure 24b).

CD measurements from 2013 and 2022 do not seem to have any major correlation ($\rho = 0.39$) with each other (Figure 25a). Distribution of field-measured CD change demonstrated in Figure 25b explains the lack of strong relationship. Some of the measured crowns have expanded in size, but some have diminished. Statistics for CD change are shown in Table 7.

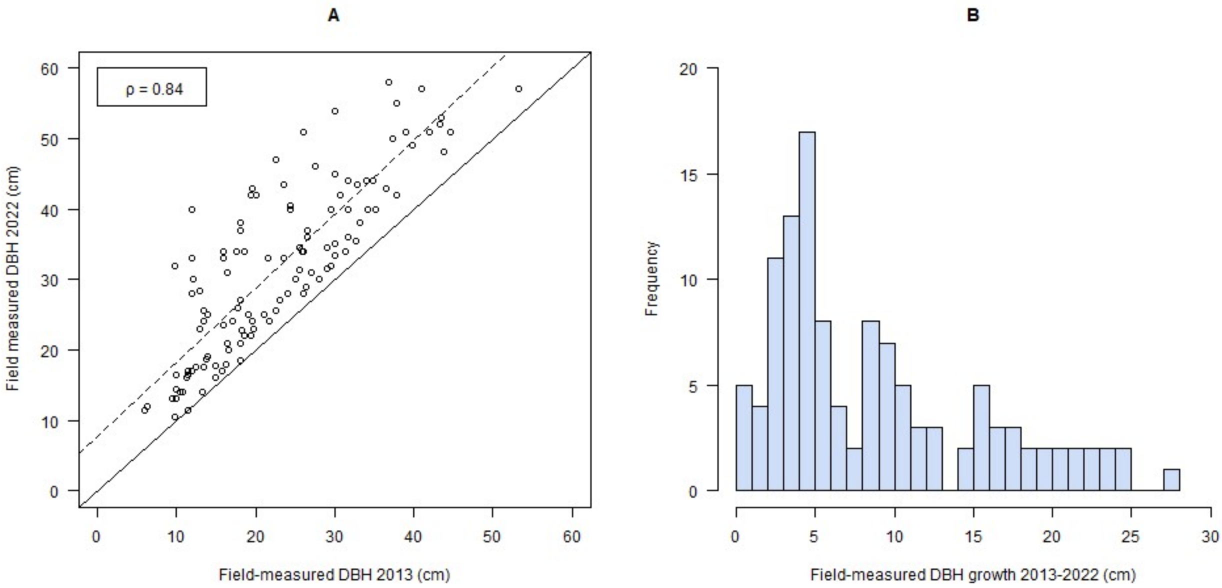

Figure 24. (a) Comparison of field-measured DBH measurements from 2013–2022 and (b) distribution of field-measured DBH growth during 2013–2022 (n=118).

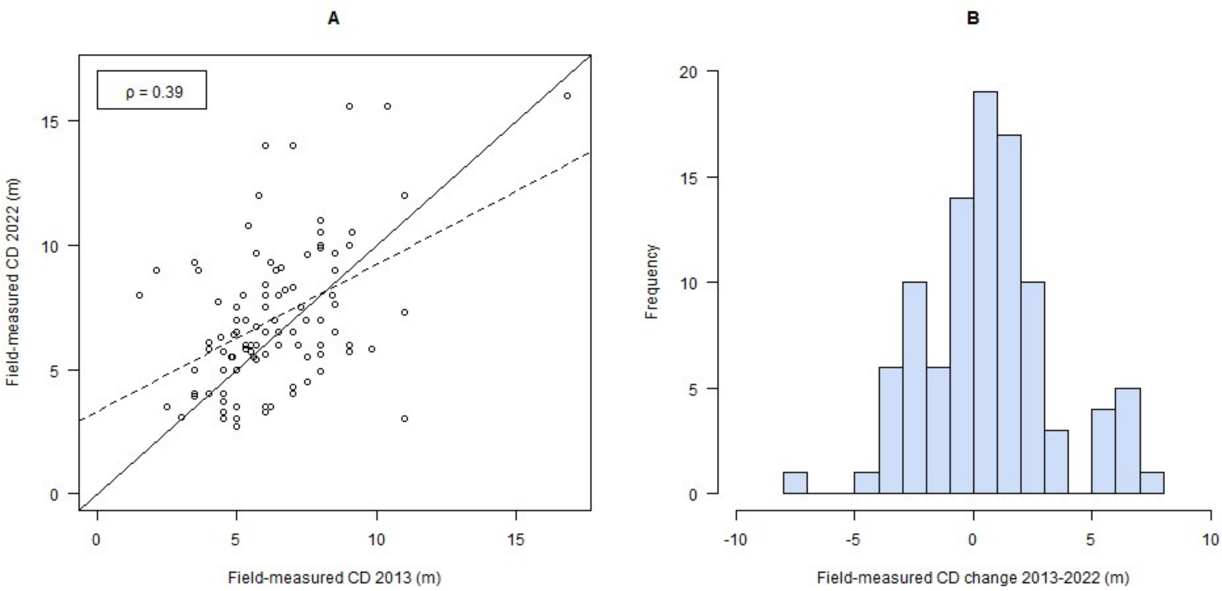

Figure 25. (a) Comparison of field-measured CD measurements from 2013–2022 and (b) distribution of field-measured CD change between 2013–2022 (n=97).

Table 7. Statistics for DBH and CD change in field during 2013–2022.

	Min.	1st Qu	Median	Mean	3rd Qu.	Max.
DBH change	0.0	4.0	6.5	9.0	12.3	28.0
CD change	-8.00	-0.90	0.5	0.5	0.5	0.5

For validation of ALS-based analyses, changes in the number of trees in plots were compared to ALS-derived mean canopy height and canopy cover change within the area of each plot. According to Figure 26, the number of measured trees has been both increasing and decreasing quite evenly. Statistics for the change of measured trees support this observation (Table 8).

The relationship between the change in the number of measured trees with mean canopy height change from CHM and canopy cover change are demonstrated in Figure 27. Both had moderate correlation with change in the number of trees: $\rho = 0.43$ for mean canopy height change and $\rho = 0.32$ for mean canopy cover change. Field-detected changes in the number of trees were usually linked to ALS-derived mean canopy height and canopy cover changes in the plot: decrease in canopy height and canopy cover was usually possible to be explained by tree loss detected in field and vice versa. More profound analyses reveal that similarity was the highest when significant number of trees had been lost from the plot. In these cases, tree loss was well distinguished also in ALS derived mean canopy height and canopy cover changes. However, if there was only slight decrease in the number of trees in the plot, it was not notable in the ALS-derived canopy height and canopy cover changes, since with a high probability, other trees in the plot have gained more height and width leading to increases in the mean canopy height and canopy cover. In some cases, there were considerable increase in the number of trees in the plots, but canopy height had still been decreasing. Usually in these plots, one taller tree had been cut down and several shorter ones had been planted. As new trees were shorter than one taller tree, the mean canopy height of the plot has been decreasing. Generally, planting new trees had a negative effect on the mean canopy height, but positive effect on the mean canopy cover.

Table 8. Statistics for the change of measured trees per plot.

	Min.	**1st Qu**	**Median**	**Mean**	**3rd Qu.**	**Max.**
No. of measured trees per plot	-14.0	-2.0	-0.96	-0.71	2.75	8.0

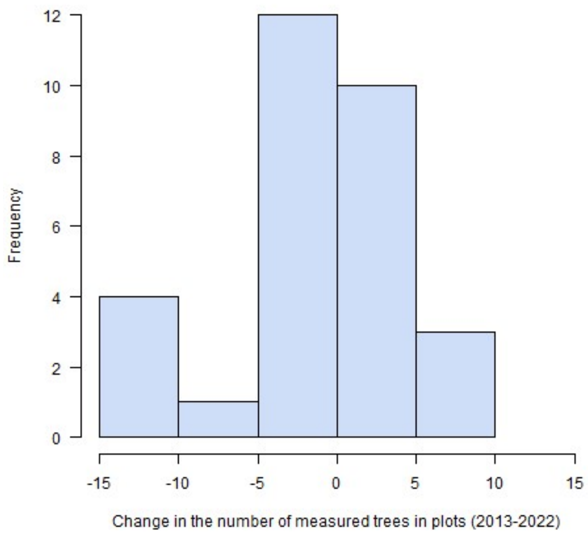

Figure 26. Distribution of the change in the number of trees per plot during 2013–2022.

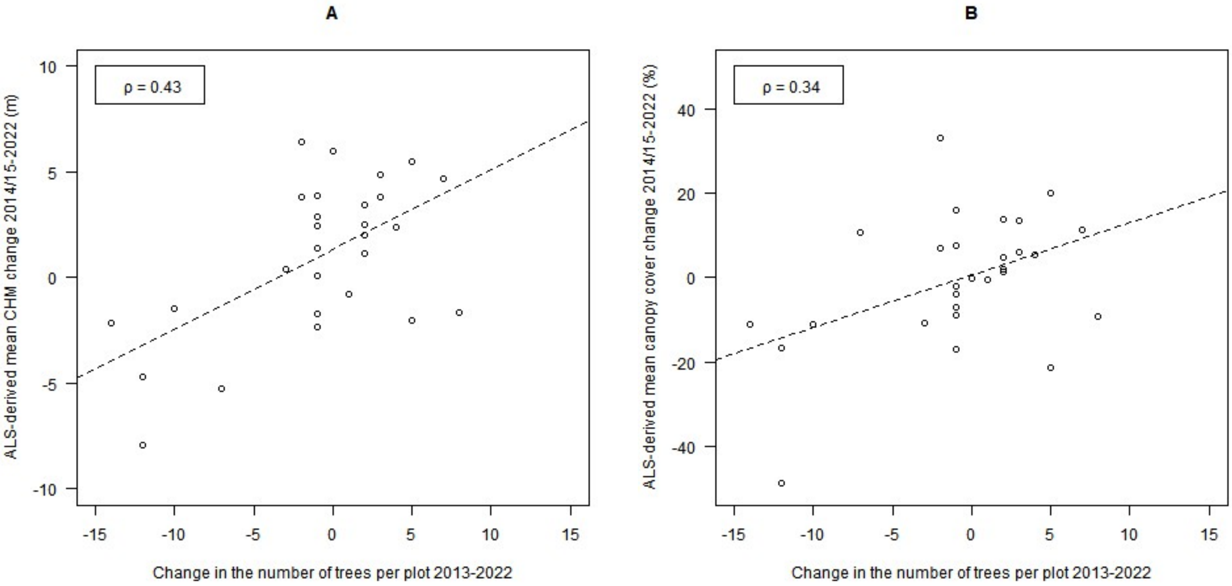

Figure 27. Comparison of change in the number of trees per plot to ALS-derived (a) mean canopy height change and (b) mean canopy cover change within each plot.

6 Discussion

6.1 Changes in canopy height and canopy cover in the study area

Multitemporal ALS data from 2014/15 and 2022 was used to detect canopy height and canopy cover change in the Taita Hills. Main objective of this study was to detect how canopy height and canopy cover have changed in the croplands during the study period. Using SPOT satellite images, tree cover in croplands has been detected to been increasing in the beginning of 21st century due to increasing tree planting on fields (Pellikka et al., 2018) but have canopy height and canopy cover continued the increasing trend during the study period based on ALS data? Analysing canopy height and canopy cover can be used to predict and estimate the benefits of agroforestry for environment and smallholders in the surrounding areas (FAO, 2022; Wang et al., 2019). It is assumed that benefits of agroforestry increase as canopy height and canopy cover in the study area increase.

Canopy height and canopy cover were found to be increasing during 2014/15–2022. Results of this study prove that increasing trend in tree cover in croplands detected by Pellikka et al. (2018) has been continuing in Taita Hills. Results also continue the global trend in the increase of tree cover in agricultural lands during 2000–2010 (Zomer et al., 2016).

Globally, agricultural land with at least 10% tree cover increased by 2% during 2000–2010 being 43% by the end of the decade (Zomer et al., 2016). In this study, the agricultural land with at least 10% tree cover increased by 24 ha which meant that 68.0% of the area outside forest had at least 10% canopy cover. Results indicate successful tree cover increases in the Taita Hills indicating that Kenyan policies supporting tree planting at least 10% tree cover in croplands has been achieved (Republic of Kenya, 2019) even though adoption of agroforestry practices have not been successful in all of Africa due to many challenges (Mbow et al., 2014).

Based on 99th percentile canopy height, canopy height and canopy height change values were higher compared to CHMs. Results were still very similar. However, the canopy height increase ≥ 2.0 m was detected in a considerably larger area based on 99th percentile canopy height change than based on CHM change. Reason for this might be the different approach used to acquire canopy height for raster cells. They do not only differ by their raster size but also the tree heights per raster cells are acquired using different methods: 99th percentile canopy height gets its value from the maximum of heights within 10.0 m × 10.0 m raster cells. Thus, 99th percentile canopy heights are presumably higher than heights from CHM.

Using lower resolution such as 10.0 m × 10.0 m, which was used in the 99th percentile heights, helps to reduce artifacts common for multitemporal ALS studies, such as wind moving branches and stems of taller trees (Nunes et al., 2021). In 1.0 m resolution, other errors might occur when lateral canopy growth has been incorrectly interpreted as a canopy height increase. In these cases, outer pixels of canopies get greater values for canopy height change even though canopy height from ground has not actually increased. This situation is described in Figure 28. When lateral growth is wrongly interpreted as canopy height increase, detected canopy height and canopy height changes from CHM are estimated higher and more common than they actually are. Lower point density in 2014/15 might have caused more inaccuracies in the canopy edges compared to 2022 data, which might have falsely increased the occurrence of lateral growth in the canopies (Senécal et al., 2018). Using lower resolution like 10.0 m instead of 1.0 m decreases the possibilities for errors caused by lateral growth. Even though using CHM and 99th percentile canopy height to detect canopy height changes are not completely comparable with each other due to different logic behind the approaches, both methods had similar results which confirms that canopy height has been increasing during the study period.

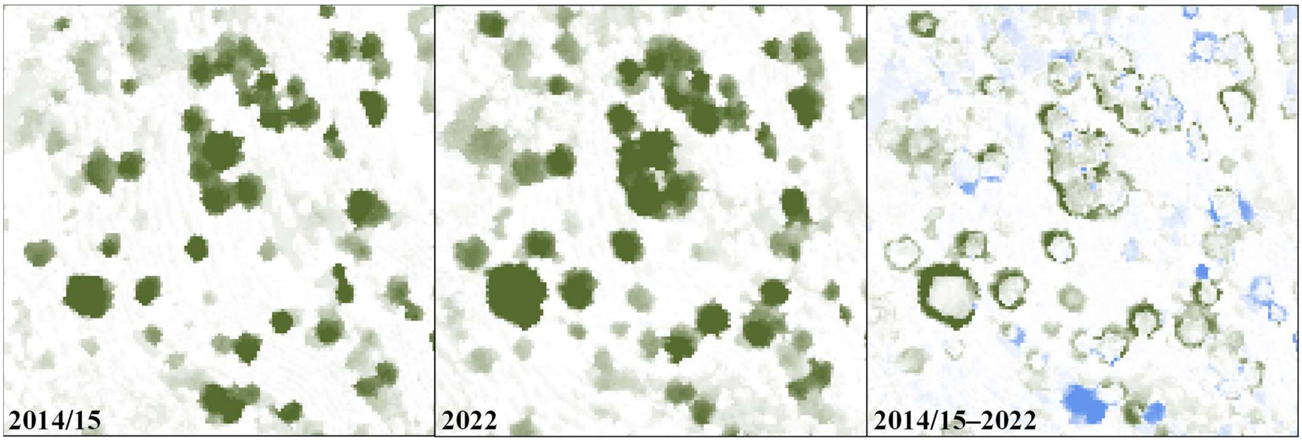

Figure 28. In CHM change between 2014/15 and 2022, lateral growth of canopies is interpreted as canopy height growth.

Even though increasing trend in canopy height and canopy cover was detected, both positive and negative change were identified. There were also areas detected where it was barely possible to identify any change in canopy height and canopy cover and where vegetation heights were stable. Even though vegetation classified as forest and buildings were masked out from the study area, the area still contained land use types such as roads where neither negative nor positive change in canopy attributes were not even expected. Both canopy height and canopy cover change were identified to have similar trend in same places, which supports the accuracy of the results at a landscape scale.

Variance in increase of canopy height and canopy cover increases was identified. In some parts of the study area, canopy attributes had grown more rapidly than in other parts of the area. How much trees grow in certain period depends on different environmental factors and tree species-specific growth rates (Callaham, 1962). Exotic tree species, which are common in the region, are especially fast growing and grow faster than indigenous ones (Gassner & Dobie, 2022). More profound study would probably reveal that areas with most rapid tree growth consisted of exotic tree species. Nunes et al. (2021) have found out that woody vegetation near rivers grows faster than trees on top of the hills. Such differences in environmental factors could also affect tree height change differences within the study area. Due to the size and complexity of the study area, there is variance in weather patterns, elevation, and steepness of the slopes, which determine the tree growth rates in the study area.

Detected decreases in canopy height and canopy cover can be consequences of several factors. According to Nunes et al. (2021), ALS detected canopy height loss can be caused by loss of trees but also by leaf and branch losses. These also cause changes in canopy cover. Tree and branch losses are typical in the regions under human use and agroforestry practices. Tree cover can have temporal variance for example due to cutting down trees for timber or firewood (Charles et al., 2013; FAO, 2022). Branches can be cut as a part of tree management practices common for agroforestry (Gassner & Dobie, 2022; Tscharntke et al., 2011). Trees can also be cut down due to changes in land use practices when cropland will no longer be under agricultural use. In addition, weather conditions can dry leaves or break branches. All these reasons decreasing canopy height and canopy cover in landscape level were witnessed during the fieldwork carried out in the study plots. It was evident that agroforestry regions are constantly experiencing changes in tree cover.

Decrease in forest cover was also discovered. Forest area decreased from 418 ha to 383 ha during the study period. Results contradict with prior study which detected increase in forest cover in recent decades (Pellikka et al., 2018). In opposite to prior study, forest classification was executed only based on ALS data in this study, which could explain the differences with prior studies in change detection of forest cover. In addition, results are not comparable due to differences in the size of the study area between these two studies. If forest cover in the whole area of Taita Hills was detected in this study, results could be different.

6.2 Validation of ALS-based analyses

The validation of ALS-based analyses was executed by comparing ALS-derived tree heights from CHM and field-measured tree heights and their tree height changes. ALS-derived tree height measurements generally correlated well with field-measured tree heights. However, ALS was found to underestimate tree heights in 2022 and tree height changes compared to field-measured heights. ALS underestimating tree heights in 2022 can be easily explained by laser beam rarely hitting the top of the canopy (Hyyppä et al., 2003b). ALS-measurements from 2014/15 were higher than field-measurements from 2013 due to 1-2 years difference in time but they are also underestimations of actual tree heights in 2014/15. The 2014/15 and 2022 ALS data have different point densities and thus they underestimate tree heights differently. ALS-derived tree heights from 2014/15 are probably more underestimated than tree heights from 2022 due to lower point density in 2014/15 (Zhao et al., 2018). Underestimating tree heights also caused inaccuracies in tree height changes since ALS also underestimated tree height changes in this study.

Even though ALS commonly underestimates tree heights, field-measured tree heights can also be highly influenced by difficulties in measuring them in field, especially with taller trees. ALS-measured tree heights from 2014/15–2022 had higher correlation than field-measured tree heights from corresponding years, which can also be explained by difficulties and uncertainties faced in measuring trees in field. Having a clear view to the base of the tree and top of the crown is necessary to have accurate height measurements. Sometimes the base of the tree or the top of the canopy can be blocked by dense vegetation. While using laser range finder, as in 2022, laser beam can hit dense vegetation instead of tree trunk, which leads to underestimation of distance to a tree and also underestimation of tree height (Hunter et al., 2013). During the fieldwork, steep hills and terraced lands made it sometimes even more difficult to have clear view to the base of the tree and top of the canopy. Slope could have caused inaccuracies especially in 2013 when clinometer was used, since measured distance to trees can be overestimated due to steep slopes (Hunter et al., 2013). Wang et al. (2019) noticed the same difficulties in measuring tree heights as was noticed during the field work. They also noticed that sometimes the crown of the tree can be too wide and complex which also makes the height measurement challenging. Height measurements for trees higher than 20–25 m seemed more scattered than for shorter trees. Wang et al. (2019) also reported that that the accuracy for field measured height decreased with trees taller than 20 m. Taller trees were more difficult to measure during fieldwork since they were more often blocked by other vegetation and since it was more difficult to get clear view to a whole tree in steep terrain.

Measuring tree height can have more chances for error than measuring other tree attributes such as DBH (Luoma et al., 2017). Collecting other tree measurements is also beneficial since they can be used to predict other tree attributes such as biomass alongside with tree height (Wang et al., 2019). Thus, DBH and CD were also measured for all trees with DBH ≥ 10 cm. Comparison of DBH measurements from 2013 and 2022 supported tree growth even though results for CD were inconsistent. Measuring CD can be also affected by difficulties in field due to challenging terrain. The shape of the canopy is rarely circular and thus challenging to be measured. In addition, cutting down branches for firewood or pruning can cause inconsistent decreases in CD measurements.

Another validation of ALS-based analyses was executed by comparing changes in the number of trees per plot to ALS-based mean canopy height and canopy cover changes within the plot. Successful results were received if significant number of trees or all the trees of the plot had been cut down during the study period. However, by using this method, validating small changes in the number of trees in plot would be difficult since other trees still gain more size over time or can be managed and trimmed by smallholders. Mean canopy height and cover in the plot can also be affected by taller crops such as banana, which were not classified as trees during the fieldwork (Heiskanen et al., 2015). Hence, plots with detected tree loss could still have higher canopy change metrics if there were, for example, bananas or maize planted during the study period. Pellikka et al. (2018) also pointed out that since only trees with DBH ≥ 10 cm were measured, other woody perennials above 2.0 m height threshold with DBH < 10 cm are not included in the change of number of trees even though they have considerable effect on ALS-derived canopy height and canopy cover in plot. All in all, changes in plots' mean canopy height and canopy cover based on ALS data were possible to be explained by field data.

Mean change in the number of trees per plot during 2013–2022 was negative meaning that in most plots there were less measured trees in 2022 than in 2013. These results suggest that tree loss would have been dominant trend in study area. That can be explained by the fact that typical agroforestry species, *Grevillea robusta*, planted in 1990s in the croplands have been cut for income generation or for building material during recent decade, while new seedlings are planted. However, such conclusions cannot be drawn based on these results only since visited plots were chosen based on the expected change in tree cover. In addition, 28 field plots is a somewhat small sample to draw any major conclusions on tree cover changes in croplands.

6.3 Current state of agroforestry in Taita Hills

The results provided new knowledge about the state and trends of agroforestry in the study area. At the beginning of 2010s, it was acknowledged that people in the Taita Hills have shown positive attitude towards planting more trees on croplands (Githiru et al., 2011). Positive attitudes towards planting trees in croplands can be recognized in the slight increases in canopy height and canopy cover. Results indicate that agroforestry is still an important farming method in the studied part of the Taita Hills and that people are motivated to practice agroforestry. However, increases in canopy height and canopy cover have not had positive relationship with forest cover. Even though forests should be less likely to be taken under agricultural use when agroforestry becomes more common (Nair, 2011), results indicate that forest cover loss has been ongoing in the Taita Hills during the study period. However, increase in forest cover has been detected in previous decades (Pellikka et al., 2018). Considering the high biodiversity and endemicity of Taita Hills, changes in forest cover should be monitored regularly in the future.

Majority of trees measured during the field work were exotic despite peoples positive attitudes towards indigenous species (Githiru et al., 2011). Utilization of exotic tree species indicates that smallholders have particularly chosen the species to use them for their high agroforestry potential. However, due to their invasive nature, exotic tree species threat indigenous species in the area (Gassner & Dobie, 2022). Thus, increase of tree cover in croplands might still lead to negative impacts on environment and biodiversity if tree cover is increased by planting exotic trees only. However, it is uncertain if invasive exotic tree species like black wattle are planted on purpose on the croplands or if they have been spreading naturally (Piiroinen et al., 2018). Even though replacing exotic trees with indigenous ones could be beneficial for environment, it might not be beneficial for smallholders since then they would miss the multiple economic benefits provided by fast growing exotic tree species.

It should be acknowledged that increases in canopy height and canopy cover in the croplands is not always reflecting positive trend in actual agroforestry practices. These changes could also represent conversion of croplands when they are abandoned for tree cultivation by the smallholder or left as fallow for several years (Pellikka et al., 2018). Croplands converted into a bushland were also identified by Teucher et al. (2020). Abandoned croplands were witnessed also during the fieldwork. Thus, some of the detected canopy height and canopy cover changes in this study, could also be caused by croplands turning to bushland.

6.4 Improvements and possibilities for future research

More precise land cover classification for agriculture and agroforestry could have been helpful in this study. Defining areas under agriculture based on ALS data was difficult due to complexity of agroforestry systems and land use practices in Taita Hills. Piiroinen et al. (2015) also acknowledged difficulties in monitoring agroforestry just based on remote sensing data. Detecting areas under agroforestry is especially challenging due to complexity of agroforestry systems: the composition of trees and shrubs can have high spatial and temporal variety in agroforestry systems (Mbow et al., 2014; Nair, 1993) and tree cover can vary from very low to very high (Zomer et al., 2009). More profound land cover classification would have helped in the classification of agroforestry areas and improved the accuracy of the results. Thus, this kind of land cover classification should be produced in the near future.

This study already provided valuable knowledge on the state and trend of agroforestry in Taita Hills. However, having more field plots covering wider area in the highlands would have given even more knowledge and generalized understanding of agroforestry in the area. Future studies could have more field plots from highlands but could also include field plots from lowlands to be able to compare differences in tree cover between these two areas.

Smallholders' attitudes towards agroforestry would be needed to provide other perspectives on changes in agroforestry. Why are smallholders planting new trees and why not? Smallholders' perspective would broaden the knowledge of the state of agroforestry, and it would provide valuable information for decision makers on how their policies are acting. It would also be beneficial to study if agroforestry has enhanced food security and sustainable agriculture in the region. If not, other actions to enhance food security and sustainability should be considered.

It has been recognized by Atzberger (2013), that the focus of remote sensing should be turned more on the agricultural practices in general, due to the issue already acknowledged at the beginning of this study: the need to intensify food production for growing demand without adding harmful effects of agriculture on natural environment (Godfray et al., 2010). Hence, the potential of remote sensing and especially the potential of ALS in studies of sustainable farming practices should be investigated and utilized more in general.

7 Conclusions

This thesis provides information and knowledge of the current state of agroforestry in Taita Hills. Canopy height and canopy cover can be used to predict and estimate the benefits of agroforestry for environment and smallholders in the surrounding areas. Thus, it is important to study changes with these parameters regularly to get information of current trends of agroforestry in the study area.

The results of this study indicate that there have been slight increases in mean canopy height and canopy cover during 2014/15–2022. Almost fifth of the area outside forests had ≥ 2 m increase in the canopy height but also areas with tree loss were detected. The area outside forest with ≥ 10% canopy cover was also detected to been increasing. Even though canopy height and canopy cover had increased in the croplands, elsewhere in the study area deforestation has been taking place. In the validation of ALS-based analyses, it was notified that ALS and field measurements matched well with each other. However, ALS data was found to underestimate tree height changes. ALS based mean canopy height and canopy cover changes in the plots predicted the actual changes well if large number of trees have been cut down during the study period.

ALS was found to be a useful method in change detection of agroforestry in larger study area even though classifying different land use types ended up being difficult in such a complex landscape. Results of this study were mainly positive, indicating that there has been a positive trend in canopy height and canopy cover in the croplands in Taita Hills. Results can be used in further agroforestry studies in Taita Hills to discover solutions for sustainable agricultural intensification in the area.

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