

DISSERTATION

BROAD-SCALE MONITORING OF CANOPY STRUCTURE WITH
MULTI-SOURCE REMOTE SENSING AND ALTERNATIVE REFERENCE DATA

Submitted by

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ABSTRACT

BROAD-SCALE MONITORING OF CANOPY STRUCTURE WITH MULTI-SOURCE REMOTE SENSING AND ALTERNATIVE REFERENCE DATA

In a time of shifting disturbance regimes and anthropogenic pressures, effective management of forest and woodland ecosystems depends on continuous, landscape-level monitoring of canopy structure. While remote sensing can help meet this need, its broad operational implementation is often impeded by a myriad of data constraints, necessitating careful tailoring of monitoring programs to specific management objectives across heterogeneous environments. For example, certain regions, such as African savannas, are heavily data-limited and present unique challenges for detecting subtle structural variations within sparse, low-stature vegetation. Conversely, data-rich regions introduce complexities in reconciling disparate reference datasets created with varied methodologies. Furthermore, widely available 3D remote sensing resources like digital aerial photogrammetry (DAP) remain vastly underutilized, despite directly measuring fundamental attributes like canopy height. A final, critical gap is that remote sensing maps are rarely evaluated for one of their primary intended applications, which is aiding in the estimation of population means or totals for vegetation attributes over distinct management areas.

To address these gaps, this dissertation investigates the strategic integration of multi-sensor remote sensing and diverse reference datasets across forest and savanna ecosystems. Crucially, each investigation moves beyond map development to evaluate how these products improve population estimates of vegetation structure using post-stratified and small area estimators. This hybrid approach empowers land managers and forest inventory programs by pairing time-series maps that visualize continuous landscape dynamics with rigorous statistical estimates that deliver defensible, population-level metrics for adaptive decision-making. The first chapter evaluates combining remote sensing predictors from multiple sources for extending canopy measurements from spaceborne waveform lidar (GEDI) across data-limited African savannas. By combining optical time series, synthetic aperture radar, and environmental covariates, parsimonious models successfully quantified annual structural changes from

herbivory and woody encroachment, though the estimated magnitude of change was muted. The second chapter examines how the selection of canopy cover reference data for building Landsat-based canopy cover maps ultimately influences the precision of population estimates of forest area and aboveground biomass in the Rocky Mountains. Comparing diverse field, aerial, and lidar-based canopy cover sources revealed that the efficiency of post-stratified estimators for aboveground biomass is driven primarily by the plot-level correlation between the reference data and the target variable, rather than marginal improvements in mapping accuracy. Finally, the third chapter demonstrates the operational viability of multi-temporal DAP for statewide forest structure estimation and post-fire canopy change assessment. While DAP struggled to capture residual standing dead stems and sparse woodlands at high resolutions, spatial aggregated canopy height models closely matched airborne lidar benchmarks and achieved nearly identical precision in statewide aboveground biomass estimation. These investigations together advance broad-scale operational use of remote sensing in diverse and complex environments to support forest inventories and effective land management.

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INTRODUCTION

Forests and woodlands play a critical role in regulating global biogeochemical cycles, supporting biodiversity, providing wildlife habitat, storing carbon, and provisioning a range of other ecosystem services (Brockhoff et al., 2017; Pan et al., 2011). The primary factor governing these functions is vegetation structure, which is characterized by attributes such as aboveground biomass, canopy height, canopy cover, horizontal tree arrangement and vertical complexity (McElhinny et al., 2005). Forest landscapes are highly dynamic and increasingly facing changes in structure due to shifting disturbance regimes, woody encroachment, and intensified anthropogenic pressures such as fragmentation (Fischer and Lindenmayer, 2007; Seidl et al., 2017; Stevens et al., 2017). Managing forests to sustain ecosystem services therefore requires a detailed and evolving understanding of structural conditions and change across diverse landscapes (Brockhoff et al., 2017).

Addressing these challenges depends on adaptive management frameworks that rely on frequent and accurate monitoring of vegetation structure over time (Westgate et al., 2013). Historically, forestry and land management have relied heavily on traditional field-based inventories, such as the Forest Inventory and Analysis (FIA) program in the United States, which can offer critical strengths including reliable ground-truth measurements and well-designed sample schemes that enable statistically rigorous estimates of many forest health attributes in addition to structural variables (Lister et al., 2020). Despite these strengths, field inventories are limited by their sparse spatial and temporal sampling frameworks and high logistical costs, constraining their ability to capture rapid, spatially heterogeneous changes in vegetation structure. Consequently, land managers increasingly require spatially continuous, near-real-time information on structural change over broad extents to support planning, monitoring, and decision-making (Camarretta et al., 2020).

Satellite optical remote sensing systems, such as Landsat and Sentinel-2, have established a foundational role in landscape monitoring to bridge this data gap (Wulder et al., 2022). While these systems were historically utilized primarily for single-date mapping or simple two-date change detection, the field has undergone a paradigm shift toward regular, continuous monitoring facilitated by freely available data, major improvements in cloud computing and advanced time-series algorithms (Woodcock

et al., 2020). Despite these advances, this form of optical remote sensing remains fundamentally limited because it only provides an indirect proxy for vegetation attributes related to vertical structure and its signal often saturates in environments with high leaf area index or biomass (Lu, 2006). These limitations necessitate the integration of three-dimensional remote sensing approaches capable of directly measuring vegetation structure.

Active remote sensing with airborne lidar has quickly become the benchmark for measuring canopy structure due to its ability to accurately capture canopy height, canopy cover, and vertical complexity (Lefsky et al., 2002). However, its high acquisition costs drastically limit spatial coverage and temporal frequency, inhibiting its operational utility for large-area monitoring (Coops et al., 2021). More recently, spaceborne lidar systems like the Global Ecosystem Dynamics Investigation (GEDI) have expanded the availability of canopy structure measurements globally across multiple years, though the sampling-based design results in discontinuous spatial coverage that limits direct application for stand-level or management-unit decision-making (Coops et al., 2021). Digital aerial photogrammetry (DAP) provides a complementary approach to airborne lidar, offering broad spatial coverage and frequent revisit intervals from aerial imaging programs in the United States and many other countries, but it relies on accurate terrain models for height normalization and is subject to limitations such as an inability to capture canopy interiors, small gaps, and isolated trees (White et al., 2013). No single sensor currently provides the combination of accuracy, spatial completeness, and temporal frequency required for operational monitoring.

Understanding the unique strengths and limitations of each sensor is essential for selecting appropriate data and executing multi-sensor data fusions that improve canopy structure mapping (Lefsky and Cohen, 2003). High-accuracy measurements from airborne or spaceborne lidar can be used as reference data to extend structural metrics across broad areas using moderate-resolution optical and radar imagery, sometimes operating as a two-step process scaling from field data to lidar, and then to satellite imagery (Hudak et al., 2020; Vogeler et al., 2023). The expanding coverage of lidar-based digital terrain models enables combination with more frequently updated DAP point clouds for height normalization, capitalizing on the fact that ground terrain remains relatively static over time (Stoker and Miller, 2022). Additionally, airborne lidar and other high-fidelity datasets can serve as critical validation

sources for satellite-derived products (Potapov et al., 2021). These data integration strategies represent a pathway toward scalable and temporally consistent mapping of canopy structure.

Generating spatially explicit maps of canopy structure is insufficient unless these products can be integrated into operational frameworks for monitoring and management. Monitoring tools capable of quantifying canopy structure changes in response to disturbance can be essential to optimizing on-the-ground responses such as silvicultural treatments, slope stabilization, and salvage logging. These tools can best serve manager needs and receive adoption when developed through a collaborative framework (Fleming et al., 2023). Moreover, these products can support national forest inventories through improving the precision of population estimates for related vegetation attributes like biomass across spatial scales or supplementing inaccessible field plots (Lister et al., 2020). Crucially, the effectiveness of remote sensing products like canopy height and canopy cover maps in these applications depends not only on their accuracy but also on their functional relationship to other variables of interest, like forest volume and basal area, and on identifying the appropriate scale of measurement (Westfall et al., 2021).

The challenges of monitoring canopy structure are especially pronounced in semi-arid woodlands and savannas, which represent a key focus of this dissertation. In these ecosystems, low and heterogeneous tree cover, short-stature woody vegetation, and complex disturbance dynamics create significant challenges for remote sensing. In optical remote sensing of savannas, the signal of woody vegetation structure can be weak relative to background variability, leading to high uncertainty particularly when evaluating changes (Reinhardt et al., 2020). In this environment DAP may also struggle to measure canopy height because of its lower accuracy than airborne lidar and aforementioned limitations with sparse trees (White et al., 2013). Spaceborne lidar systems like GEDI are also unable to resolve height below about 2.5 m (Li et al., 2023), a common canopy height in many savannas, and they confound the canopy and ground laser return on high slopes (Gwenzi and Lefsky, 2014). These signal-to-noise challenges necessitate targeted methodological approaches and careful evaluation of model bias and uncertainty.

The overarching goal of this dissertation is to evaluate and advance strategic combinations of remote sensing data for mapping canopy structure and detecting structural changes to support sustainable land management. This work emphasizes the development of broad-scale operational

monitoring frameworks to be applied across diverse and complex landscapes. To that end, a specific sub-focus is dedicated to solving the unique measurement and mapping challenges inherent to semi-arid woodland environments like African savannas and US pinyon-juniper woodlands. A central theme throughout these investigations is the role of scale, both in terms of spatial resolution and the scaling of information from field plots to landscapes and regions, and how scale influences the accuracy and applicability of remote sensing products.

This research is motivated by several key gaps in both scientific understanding and operational application of remote sensing. First, there is a need for robust multi-sensor fusion approaches tailored to data-limited, semi-arid systems, where structural changes are subtle and difficult to detect, yet critically important for management. Conversely, in regions with an abundance of reference data but from different sources, datasets may rely on inconsistent definitions and measurement techniques for attributes like canopy cover, which increases the difficulty in selecting or combining different sources in remote sensing modeling to support downstream applications. Third, while canopy height is often a stronger predictor of some vegetation structure attributes than canopy cover, it remains less widely available, and the potential for multi-temporal DAP to fill this gap at broad scales remains largely unexplored.

The three chapters of this dissertation address these gaps across complementary contexts. The first chapter develops and evaluates feature-level multi-sensor fusion approaches to extend GEDI-derived canopy structure metrics across savannas in the Kruger National Park region of South Africa, enabling quantification of structural changes associated with herbivory, harvesting, and woody encroachment. The second chapter investigates how different canopy cover reference datasets influence Landsat-based mapping accuracy and the resulting precision of population estimates of forest area and aboveground biomass, providing insight into the selection and combination of reference data across diverse ecosystems of the Rocky Mountains, including semi-arid woodlands. The third chapter builds on the idea of improving vegetation structure mapping and population estimates in the Rocky Mountains by investigating the operational use of canopy height maps derived from multi-temporal DAP.

Together, these chapters form a cohesive and progressive body of work that advances the operational use of remote sensing for vegetation structure monitoring in forests and woodlands. By refining multi-sensor data fusions, interrogating foundational reference data choices, and rigorously

testing widely available 3D datasets like DAP, this dissertation provides practical methodologies for integrating remote sensing into adaptive management frameworks. A recurring insight across all chapters is the scale-dependence of accuracy and the importance of aligning spatial and temporal resolution with specific monitoring objectives. Ultimately, this work seeks to enhance operational forest and woodland monitoring, track complex disturbance dynamics, and reliably support adaptive management in critical ecosystems over broad extents.

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CHAPTER 1—Tracking savanna vegetation structure in South Africa by extension of GEDI canopy metrics with Landsat, Sentinel-2, and PALSAR¹

1 Abstract

Adaptive management of savanna ecosystems requires frequent monitoring of woody vegetation structure, and although vegetation structure and changes may be captured with repeat airborne lidar, it is spatially and temporally limited across African savannas. As an alternative, this study evaluates the extension of spaceborne waveform lidar canopy metrics (RH98, Cover, Foliage Height Diversity) from the Global Ecosystem Dynamics Investigation (GEDI) across the Greater Kruger region in South Africa using moderate resolution optical sensors (Landsat and Harmonized Landsat Sentinel-2 [HLS]), L-band Synthetic Aperture Radar (PALSAR-1 and -2), and topographic and soil covariates. We compared the performance of 12 predictor sets incorporating different sensor combinations and temporal processing methods (LandTrendr and CCDC) in random forest models using temporal cross-validation to assess extrapolation accuracy. The most parsimonious fusion model (LandTrendr + SAR + topography/soils) achieved RMSEs of 3.04 m for RH98, 13.38% for Cover and 0.34 for FHD, which was comparable to more complex models using HLS and CCDC. All models demonstrated good temporal transferability with minimal bias but tended to overestimate low values and underestimate high values, which muted the estimated magnitude of change. Annual canopy structure maps derived from the best model captured expected spatial patterns and were used in model-based estimators to quantify changes in areas impacted by elephants, timber harvesting, fuelwood extraction, and woody encroachment. Extending GEDI metrics with moderate-resolution sensors thus offers a viable approach for large-scale savanna monitoring and detecting change in high impact areas.

2 Introduction

Understanding the structure and dynamics of woody vegetation is crucial for ecological management and conservation of savanna biomes, which cover approximately a fifth of the Earth's land surface and

¹ Adapted from: Filippelli, S.K., Vogeler, J.C., Mauro, F., Coetsee, C., Fekety, P.A., McHale, M., Bunn, D., 2026. Tracking savanna vegetation structure in South Africa by extension of GEDI canopy metrics with Landsat, Sentinel-2, and PALSAR. *Science of Remote Sensing* 13, 100388. <https://doi.org/10.1016/j.srs.2026.100388>

provide ecosystem services to over one billion people (Scholes and Archer, 1997; Twine, 2019). Frequent monitoring of woody structure is particularly important in savannas due to their highly dynamic nature, one that is strongly influenced by disturbance regimes. Significantly, these changes can have cascading effects on biodiversity (McCleery et al., 2018) and ecosystem function and services (Ding and Eldridge, 2024). In African savannas, remote sensing has become an indispensable tool for mapping and monitoring woody vegetation structure and its changes over time, with studies demonstrating its effectiveness in quantifying tree cover, canopy height, and biomass at various scales (see review by Abdi et al., 2022). While airborne lidar has been regarded as the most accurate remote sensing system for mapping canopy structure (Coops et al., 2021), its lack of spatial and temporal availability, particularly in African savannas, limits its application as a regular monitoring tool. Spaceborne lidar systems, like the Global Ecosystem Dynamics Investigation (GEDI), now enable regular, large-scale monitoring of woody structure across Africa's vast and often inaccessible savannas (Abdi et al., 2022; Li et al., 2023). This advancement provides critical data for addressing key conservation challenges such as woody encroachment, megafauna impacts, habitat fragmentation, and resource extraction pressures.

The region of South Africa encompassing Kruger National Park (KNP) and adjacent private nature reserves has been a focal point for studying the natural and anthropogenic factors that shape vegetation structure in savannas. Changes in elephant populations, rewilding efforts, fuelwood and timber harvesting, woody encroachment, and illegal mining are only a subset of the changes occurring in this landscape that are of interest to scientists, land managers, and policy makers alike. In KNP, elephant numbers have surged from about ~9,000 in 1994 when culling ceased to ~31,000 in 2020 (Ferreira et al., 2024), significantly accelerating tree fall, which can be six times higher in some landscapes open to elephants (Asner and Levick, 2012). After 1994, policy changes were introduced to encourage wider area rewilding efforts. These included the closing of artificial waterholes and fence removal between the park and private reserves, leading to rapid redistributions of elephant impacts (de Boer et al., 2015; Smit et al., 2007). Human activities also contribute to structural changes — fuelwood harvesting in communal areas may promote coppice growth (Shackleton et al., 2022; Twine and Holdo, 2016) and reduce the abundance of large stems and preferred species depending on harvest regimes (Matsika et al., 2013). Forest plantations in the western portion of the Greater Kruger area provide high socioeconomic value for

the region but also reduce streamflow within a catchment zone where maintaining water production and quality is a high priority (Dye and Versfeld, 2007; GKSDP, 2020). Additionally, widespread woody encroachment, likely linked to rising CO₂ levels or possibly regional changes in fire regimes or livestock management, has been observed as doubling in woody cover across land uses between 1940 and 2010 (Stevens et al., 2016). These dynamics underscore the complexity of woody structure change in this savanna landscape, further complicated by the heterogeneity and seasonal variability inherent to these ecosystems.

Quantifying the magnitude and spatial patterns of woody structure change associated with these different disturbance types and change drivers is crucial for adaptive management in the Greater Kruger region. To implement adaptive management strategies that maintain desired ecosystem states and biodiversity, managers need to know how factors such as elephants, fuelwood collection, timber harvesting, and woody encroachment are impacting woody vegetation in near-real time and across sensitive areas (Gaylard and Ferreira, 2011). Obtaining sufficient field data to accurately quantify such changes in small areas of interest using traditional estimation methods can be challenging and resource-intensive (Rao and Molina, 2015). Remote sensing-based maps provide a promising alternative for enabling comprehensive assessments of vegetation structure and its changes across spatial and temporal scales in savannas (Abdi et al., 2022).

Remote sensing-based maps of woody structure can also be leveraged to assess average levels of structure or change for specific areas of interest, often with lower uncertainty than assessments relying on field data alone (Ståhl et al., 2016). This is especially important in savanna ecosystems, which typically feature low to moderate tree cover and may have subtle changes compared to clear cutting in temperate forests. However, these factors also pose a challenge for remote sensing in savannas. The prediction error and potential biases of woody structure maps or their change may be comparable to or even exceed the magnitude of actual change (Reinhardt et al., 2020), and these issues may propagate when assessing average change for areas of interest (Filippelli et al., 2024). Furthermore, applying remote sensing models outside the temporal range of their training data, known as “temporal transferability”, introduces the potential for additional bias, which can lead to inaccurate conclusions about the amount or even the direction of change (Fekety et al., 2015; Filippelli et al., 2024). For these reasons, it is imperative

to check for model bias and quantify the uncertainty associated with remote sensing-based estimates of canopy structure and change to ensure that observed changes are real and not artifacts of model error or bias.

Previous research on remote sensing of woody structure in African savannas has provided valuable insights into methods for improving the precision of structure maps that can elucidate spatial patterns and ecosystem dynamics. Airborne lidar mapping of experimental herbivore exclosures and historical burn plots in KNP have revealed how geologic substrate, soil nutrient availability and moisture, fire regimes, and herbivory interact to influence canopy height and cover (Asner et al., 2009; Smit et al., 2010) and tree spatial patterns in savannas (Staver et al., 2019). Repeat lidar can provide greater detail and mechanistic understanding of these changes, for example by quantifying elephant treefall rates (Asner and Levick, 2012). Although limited in spatial and temporal availability, airborne lidar has also served to calibrate models based on moderate resolution sensors for broader scale monitoring. L-band SAR from the dry season has proven to be the most effective sensor for mapping of woody cover and biomass, with modest improvement in accuracy provided by fusion with optical sensors or C- and X-band SAR (Naidoo et al., 2016, 2015; Urbazaev et al., 2015). Changes in woody cover can be monitored through comparison of annual map products developed from L-band SAR, though use of direct backscatter change yields less underestimation of change and generally lower RMSE and bias (Wessels et al., 2023). These examples illustrate the critical role played by airborne lidar in helping to understand savannas at experimental sites or through extension with moderate resolution sensors. However, they are limited to the vegetation types and time periods captured in the airborne lidar. There is still a need for more frequent monitoring of woody structure over a greater diversity of vegetation types within savannas to enable adaptive management to rapidly respond to changes as they are occurring.

Sampling spaceborne lidar systems, such as GEDI, provide a potential alternative for frequent monitoring woody structure over a greater diversity of landscapes due to their spatially extensive multi-year coverage. In southern African savannas, GEDI canopy height captured during leaf-on had an RMSE of 1.64 m and bias of -0.55 m when compared to waveform simulation with airborne lidar (Li et al., 2023), proving its potential utility as an alternative reference source. GEDI relative height 95th percentile (RH95) was extrapolated with Landsat to produce a 2019 global canopy height map at 30 m resolution with an

overall model RMSE of 6.6 m, an airborne lidar validation RMSE of 9.07 m, and no airborne lidar validation in savannas (Potapov et al., 2021). GEDI L2A height metrics and L2B canopy metrics have also been expanded wall-to-wall with moderate resolution sensors in western US forests (Vogeler et al., 2023) and other regions (Geremew et al., 2024; Kacic et al., 2021), but applications in savanna systems remain limited. In one example, modeling GEDI RH95 with Landsat, Sentinel-1, and Sentinel-2 in western Australia eucalypt savannas had an RMSE of 2.68 m (Lutz et al., 2024). There remains a need to evaluate the wall-to-wall extension of GEDI canopy metrics in African savannas as has been done in other regions.

The goal of this study was to test different remote sensing data sources and approaches for mapping GEDI canopy structure metrics across the Greater Kruger region over time to enable monitoring of woody structure changes. To this end, we specifically sought to answer three fundamental questions:

1. How do moderate resolution data source and processing methods influence the accuracy in mapping GEDI canopy metrics wall-to-wall in an African savanna?
2. How do different model predictor sets affect accuracy when temporally transferring the model to time periods outside that of GEDI's temporal availability?
3. Do maps of canopy structure capture known spatial patterns and magnitude of change in areas with known elephant damage, timber removal, fuelwood harvesting, and woody encroachment?

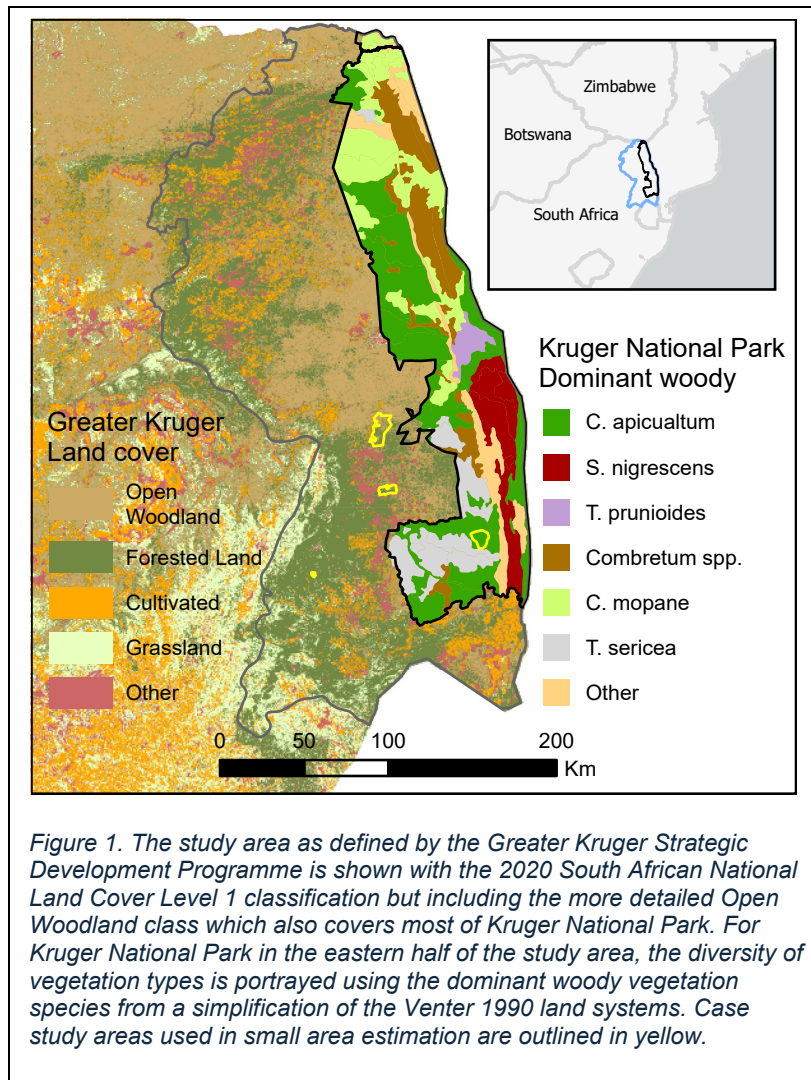
To answer these questions, we modeled the GEDI L2A and L2B canopy metrics of RH98, canopy cover, and foliage height diversity with multiple predictor sets reflecting trade-offs in temporal availability and processing complexity. These included Landsat and Harmonized Landsat Sentinel-2 processed with the LandTrendr and Continuous Change Detection and Classification (CCDC) algorithms, PALSAR-1 and -2, topographic indices derived from the Shuttle Radar Topography Mission (SRTM), and predicted soils layers from the Innovative Solutions for Decision Agriculture Ltd. (iSDA). The highest performing model was used to map annual GEDI canopy structure for the Greater Kruger region between 2007 and 2022. The maps of canopy structure were then used in model-based estimators to quantify the mean structure values before and after change events in four areas of interest with known change drivers. The results of this study will form the basis for regular monitoring of woody structure in the Greater Kruger region and inform future research for spaceborne lidar supported vegetation monitoring in savannas.

3 Methods

3.1 Greater Kruger

South Africa's Greater Kruger is a 60,600 km² region defined in this study as encompassing KNP, a collection of private nature reserves and communal lands immediately to the west, and agricultural and urban development extending to the Drakensberg mountains in the west and the southern border of Ehlanzeni district municipality to the south. The geologic parent material, precipitation patterns, and topography are the primary drivers of vegetation patterns in this region. KNP has a distinctive divide of nutrient poor granitic soils in the western half of the park and nutrient rich basaltic soils in the east. Average annual precipitation follows a gradient of generally becoming wetter (750 mm/yr) when moving towards the north or west and drier (425 mm/yr) in the south and east. The savannas in the eastern portion of Greater Kruger exist on low undulating hills that lead to flatter grassy plains going further east (150 m to 750 m in KNP), while greater relief is present in the west rising to forested mountains (up to 2000 m).

The Lowveld ecozone, which covers KNP and the immediately surrounding area, contains 35 vegetation types (Gertenbach, 1983). The most prevalent woody vegetation found across these classes include *Colophospermum mopane* dominating vast areas of the north, *Combretum spp.* more often dominating in the south, and *Terminalia spp.* covering microtopographic patches (Figure 1). Vegetation characteristics within the eastern granitic landscapes follow a topographic gradient known as a catena with different woody species typically found along sandy crests, wet seep lines, midslopes, and footslopes. Although Lowveld savannas are dominated by shrubs and short stature trees of ~2-5 m, there are sparsely interspersed tall trees (>5 m) that emerge from this matrix (e.g., *Sclerocarya birrea*, *Senegalia nigrescens*, *Adansonia digitata*). Weaving through the savanna are also riparian forests consisting of taller trees with broad crowns (e.g., *Diospyros mespiliformis*, *Ficus sycomorus*).



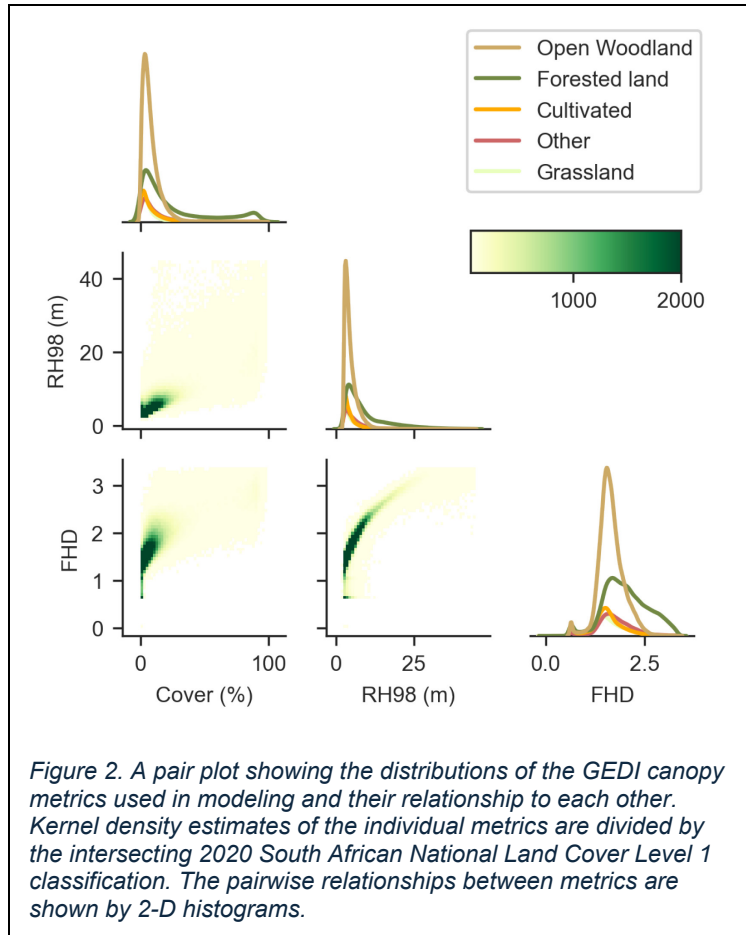
3.2 Mapping GEDI canopy metrics

3.2.1 GEDI data

We acquired the GEDI Level 2A Geolocated Elevation and Height Metrics version 2 product (GEDI02_A) and the GEDI Level 2B Canopy Cover and Vertical Profile Metrics version 2 product (GEDI02_B) for all shots collected over the study area between January 1, 2019 and December 31, 2023. These data were filtered to retain shots that had an L2A and L2B quality flag of 1 and that were collected during leaf-on (121 to 305 days of year). Li et al. (2023) found phenology to have the largest impact on GEDI canopy height accuracy in African savannas, whereas the use of coverage versus power beams or day versus night shots made no difference so long as the sensitivity was at least 90%. We extracted the

relative height 98th percentile (RH98) metric from the L2A product and canopy cover (Cover) and foliage height diversity (FHD) from the L2B product. RH98 is the 98th percentile relative height above the perceived ground elevation and is the most commonly used metric of canopy height to reduce the influence of outliers. The GEDI Cover metric can be interpreted as “the percent of the ground covered by the vertical projection of canopy material” (Tang and Armston, 2019). FHD is a equivalent to the Shannon diversity index for vertical heterogeneity of canopy elements, which is calculated by taking the proportion of leaf area index in a vertical layer and multiplying by its log and then taking the negative of the sum across all vertical layers (Tang and Armston, 2019). In African savannas, including some study areas overlapping the Greater Kruger region, GEDI RH98 collected during leaf-on had an RMSE of 1.48 m and a bias of -0.55 m when compared to airborne lidar simulated waveforms (Li et al., 2023). GEDI Cover has also been validated across forest types (X. Li et al., 2024; Y. Li et al., 2024).

We further compared GEDI RH98 to a small, opportunistic sample field measurements of maximum canopy height at select locations as an additional check of GEDI accuracy in our study area. 26 GEDI footprints in Kruger National Park were visited in January 2023, May 2023, and May 2024. We navigated to the center of the footprint with a Trimble GeoXH, which has a rated precision of 10 cm, and then used a laser range finder to measure the maximum canopy height within the footprint area.



3.2.2 Spatial predictors

We evaluated Landsat, Harmonized Landsat Sentinel-2 (HLS) and PALSAR-1/2 data as remote sensing predictors in models of the GEDI canopy metrics. The Landsat Collection 2 Level 2 Tier 1 surface reflectance product for 1984-2023 and the HLS 30 m surface reflectance data for 2013-2023 were obtained and processed in Google Earth Engine (GEE) (Gorelick et al., 2017). Because only the Landsat portion (HLS L30) of the HLS product was available in GEE, we created the Sentinel-2 portion of the dataset by applying the same coefficients for bandpass adjustment used by the HLS product (Claverie et al., 2018) and used area-weighted mean resampling to 30 m. We did not apply the Nadir Bidirectional Reflectance Distribution Function (NBAR) normalization to the Sentinel-2 data, and the cloud probability layer created with the sentinel2-cloud-detector was used for cloud masking with a threshold of 0.65. The Landsat scenes were masked to exclude clouds, cloud shadows, aerosols, and radiometric saturation using flags in the pixel quality assurance band created through the Fmask algorithm. We calculated

several spectral indices for each dataset including the Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974), the Normalized Burn Ratio (NBR) (Key and Benson, 2006), the Normalized Difference Moisture Index (NDMI) (Gao, 1996), Tasseled Cap Brightness (TCB), Tasseled Cap Greenness (TCG), and Tasseled Cap Wetness (TCW) (Crist, 1985; Huang et al., 2002).

The Landsat and HLS data were then processed with two time-series algorithms for comparison: the Continuous Change Detection and Classification (CCDC) algorithm (Zhu and Woodcock, 2014) and the LandTrendr algorithm (Kennedy et al., 2018, 2010). CCDC generates harmonic regression coefficients for each pixel and band while automatically creating break points to account for disturbances. Coefficients from CCDC capture the overall brightness and phenology of observed surface reflectance as well as its trend over time. We extracted these coefficients from the end of the year (December 31) to represent the conditions of that year. We also created synthetic reflectance values representing at the middle of the wet season (February 1st) and dry season (September 15th) to account for changes in canopy structure that occur between years but within a CCDC segment that spans multiple years. For running CCDC, we excluded scenes with greater than 80% cloud cover to reduce the possible influence of unmasked clouds. Previous large area monitoring projects have applied CCDC to only the original spectral bands (Brown et al., 2020), and so we excluded spectral indices from CCDC outputs to reduce the number of variables and processing time. LandTrendr applies a linear fit to annual composites and identifies breakpoints to create linear temporal segments that reduce between year variations that are likely not due to actual changes in canopy structure (Kennedy et al., 2010). For processing each band and spectral index with LandTrendr, we first applied temporal compositing by calculating the medoid for the wet season (October 1st to April 30th) and dry season (May 1st to September 30th). Because LandTrendr is more susceptible to the influence of clouds, particularly at the beginning and end of the time series (Kennedy et al., 2010), we excluded scenes which had greater than 50% cloud cover. LandTrendr was run on each band and spectral index independently to produce “fitted” values using default parameters but with a maximum of 6 segments and prevent one year recover turned on.

The Global PALSAR-2/PALSAR version 2 annual mosaics of L-band SAR backscatter for 2007-2010 and 2015-2022 were also obtained from GEE. This 25 m resolution annual mosaic product is created from PALSAR strip maps collected in Fine Beam Dual mode and Wide swath Beam Dual mode

with visual selection of strips to minimize the influence of surface moisture, ortho-rectification and slope correction with the ALOS World 3D digital surface model, and then radiometric balancing between adjacent strips. We converted these data from digital numbers to gamma naught and applied multitemporal speckle filtering using a boxcar spatial filter with a kernel size of 7 (Quegan and Yu, 2001), which was found to be effective in this region (Wessels et al., 2023). The HH and HV backscatter coefficients and local incidence angle were used as predictors of the canopy metrics.

In addition to the above temporally varying remote sensing predictors, we included temporally static spatial data on topography and soils as predictor variables in modeling the canopy metrics. A series of topographic metrics were created from elevation data collected by the Shuttle Radar Topography Mission (SRTM). Elevation, percent slope, aspect, the cosine of aspect, the sine of aspect, percent slope multiplied by the sine and cosine of aspect, transformed aspect, and topographic position index at 30 m, 300 m, and 990 m were all created from elevation data from NASADEM (NASA JPL, 2020), which is based primarily on SRTM. We also obtained the multiscale topographic position index, continuous heat-insolation load index, and topographic diversity index based on SRTM from Theobald et al. (2015). Predicted soils information at a 30 m resolution was obtained from the Innovative Solutions for Decision Agriculture Ltd. (iSDA) soils layers for mean organic carbon, cation exchange capacity, and nitrogen at 0-20 cm and 20-50 cm (Hengl et al., 2021).

3.2.3 *Modeling and mapping*

For compiling model training and validation data, the area-weighted mean of each predictor layer was extracted for each GEDI footprint. For the temporally varying layers based on Landsat, HLS, and PALSAR, we extracted data for the year corresponding to the GEDI collection date. The wet season was associated with the year of its start date. For example, data for 2022 includes data obtained from the dry season dates of May 1, 2022 to September 30, 2022 and wet season dates October 1, 2022 to April 30, 2023. We spatially filtered GEDI shots to reduce the sample size and avoid overly optimistic validation statistics from training and testing on adjacent pixels; this was done by randomly selecting at most one shot within 500 m square grid cells ($n=277,046$).

Twelve empirical models of the GEDI canopy metrics were developed from the above predictor data sets using random forest regression (Breiman, 2001). All random forest models used 100 trees and

at each node the square root of the total number of variables was considered for splitting. The first two models used only Landsat predictor variables fitted with either LandTrendr or CCDC (CCDC^{L30}) to enable hindcasting of vegetation structure for change analysis over longer time periods. The third model used HLS data with CCDC (CCDC^{HLS}), which offers greater temporal frequency for filling temporal gaps in the cloudy wet season and reducing artificial breakpoints, but HLS data is limited to 2015 forward. A model was created with PALSAR data only, which is limited to 2007-2010 and 2015-forward, but provides a more direct measurement of woody biomass. We also tested the fusion of each of the optical data sources with PALSAR and the topographic and soil static variables.

Accuracy was assessed for all models by the root mean square error (RMSE), coefficient of determination (R^2), and bias (i.e., mean of residuals) using withheld GEDI samples as in other GEDI extrapolation studies (Potapov et al., 2021; Vogeler et al., 2023). We use out-of-bag predictions because they provide an unbiased assessment of generalization error for random forest models (Breiman, 1996). We also implemented temporal cross-validation using withheld years of test data (Filippelli et al., 2024; Roberts et al., 2017) to estimate the accuracy of extending the models beyond the time period of the training data. Based on this accuracy assessment, we selected the best model for use in wall-to-wall annual mapping of the canopy metrics and subsequent analyses of change in woody structure.

Because predictions were extrapolated to years outside the availability of GEDI for training and testing, we also tested the sensitivity of predictions to the 2015 extreme drought event, as a complement to the temporal cross-validation analysis. Site locations from the Veld Condition Assessment, which is an annual vegetation monitoring program in Kruger National Park, were filtered to those not intersecting known fires between 2009 and 2017. A random sample of 42 sites were photo-interpreted for changes in tree cover using very high resolution satellite imagery. The 30 sites not showing change between 2010 and 2017 were used to evaluate the time series of Cover predictions for anomalies related to the drought.

3.3 Small area estimation for known areas of change

Maps of RH98, Cover, and FHD were used to assess changes in canopy structure for areas of interest, which were primarily in private nature reserves along the western border of KNP. We delineated four areas of interest with known changes using a combination of property boundaries, very high-resolution satellite imagery, descriptions in previous literature, and through consultation with local area

experts. The areas are known to be affected by elephant damage, fuelwood extraction, timber harvesting, and woody encroachment. The first site, Thornybush Nature Reserve, removed its eastern fences in 2017 to create a continuous landscape with KNP, and the elephant population increased from 55 in 2017 to 770 in 2019 (H. Zowitsky, pers. comm.), which has resulted in high levels of tree damage and mortality. Second, an area of tree plantations that underwent a series of harvests starting in 2015 was delineated in the Drakensberg mountains to the west of Kruger National Park. Third, communal lands in the Bushbuckridge area have been subject to intense fuelwood extraction in some areas, and previous research has indicated that this has mostly resulted in coppice growth (Mograbi et al., 2015). The savanna regions of GKNP have in general been undergoing woody encroachment, which is believed to be caused in part by CO₂ enrichment (Stevens et al., 2016). We delineated an area southeast of the Skukuza rest camp known by local experts to have high levels of woody encroachment, which was also noticeable in 2009 and 2024 Google Earth imagery.

Small area estimation was used to quantify the mean and construct confidence intervals of the canopy metrics for the areas of interest before and after the year the impacts occurred, or at the start and end of the canopy metrics map time series (i.e., 2007 and 2021). We used the Battese-Harter-Fuller unit-level model-based estimator (Battese et al., 1988; Rao and Molina, 2015) with the predicted canopy metric maps serving as the auxiliary data available for each unit of the population (i.e., a pixel). The model for the estimator was fit to the sample of GEDI shots used in the remote sensing model described above. We combined areas with the years in which they contained GEDI footprints to form 11 domains that were used in model-based estimation. The Battese-Harter-Fuller model is based on a mixed effects model that uses independent areas as domains, and our models, which have a temporal component, may not be as efficient in obtaining the precision of estimators. Because of this we also compared mixed effects models using area and time combined (i.e., the domains described above) with models using alternative random effects structures of area and area crossed with time.

In years without GEDI (i.e., prior to 2018), the estimator of the mean is fully synthetic and thus more likely subject to bias. The temporal cross-validation described in the previous section is intended as a check for potential bias in the estimators when they rely on canopy maps created from applying the remote sensing model outside the temporal domain of the training data. The estimators for the mean for

each domain were obtained with the empirical Bayes approach using the emdi package in R (Kreutzmann et al., 2019). Point estimates of the mean were made from 200 Monte-Carlo simulations. Models were fit with a Box-Cox transformation to better meet model assumptions necessary for estimating mean squared error (Appendix 1.2). However, we obtained mean squared error with a semi-parametric bootstrapping approach that is also robust to model misspecification (Thai et al., 2013). The mean squared error obtained from 200 bootstrap replicates was used to constrict 90% confidence intervals.

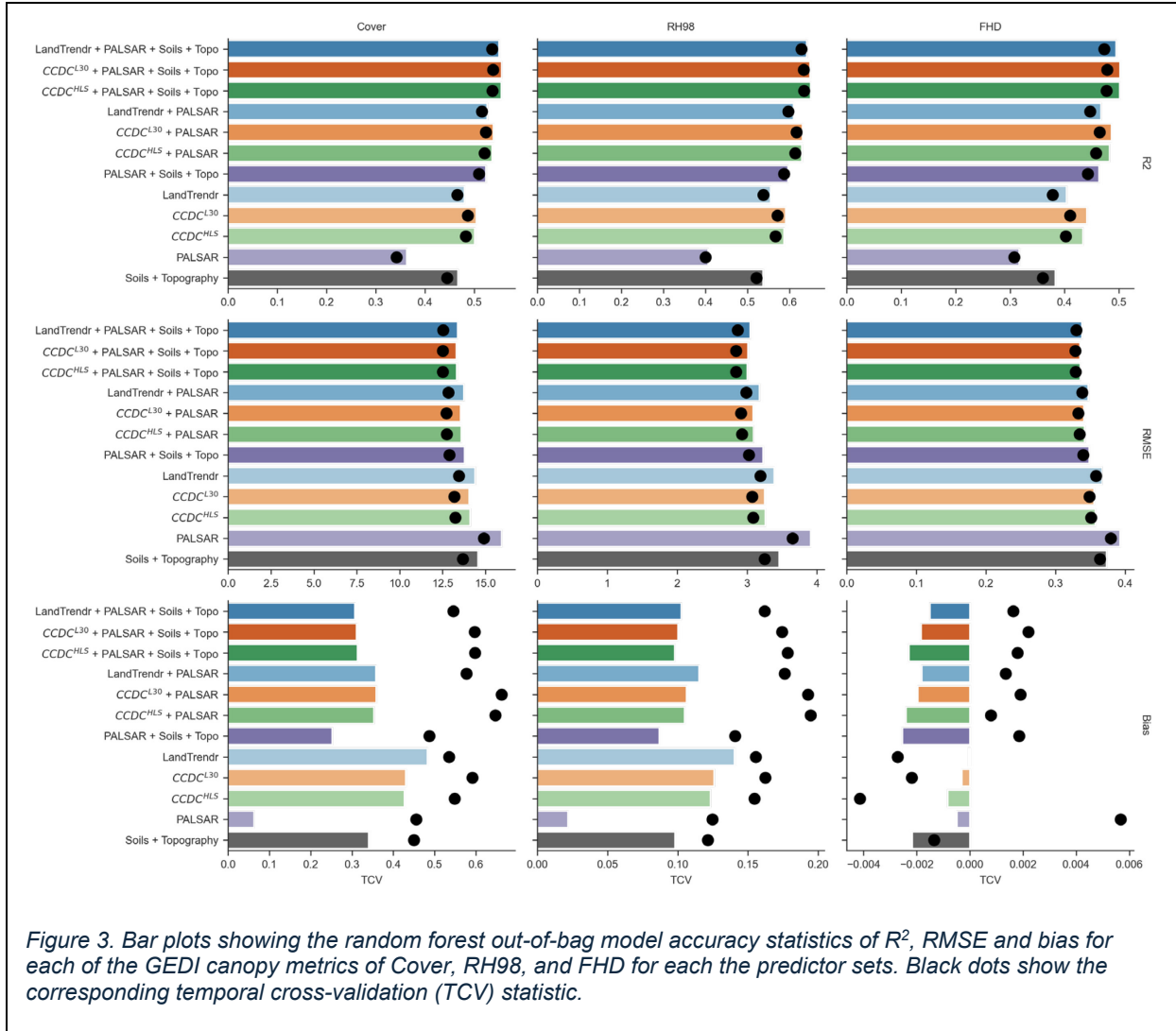


Figure 3. Bar plots showing the random forest out-of-bag model accuracy statistics of R^2 , RMSE and bias for each of the GEDI canopy metrics of Cover, RH98, and FHD for each the predictor sets. Black dots show the corresponding temporal cross-validation (TCV) statistic.

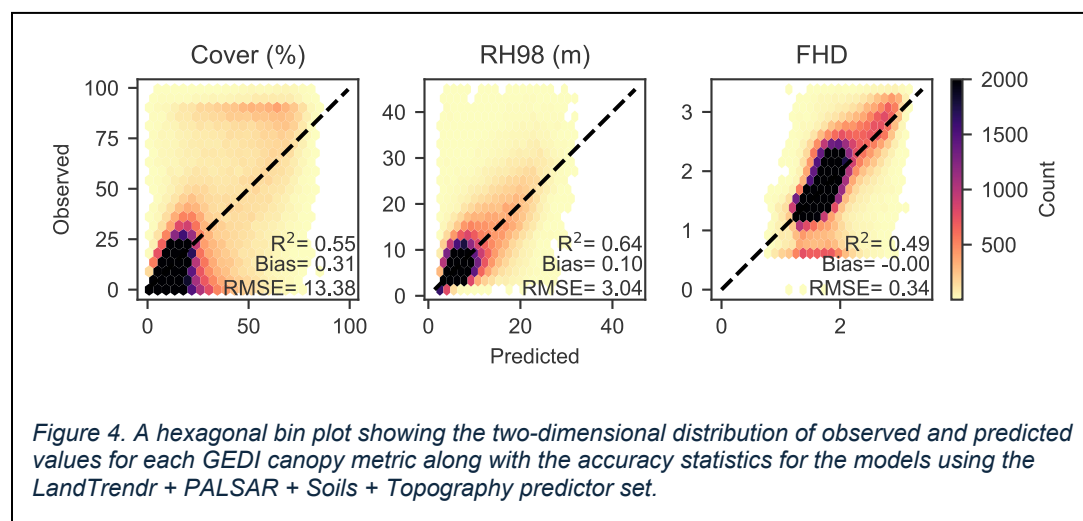
4 Results

4.1 Models of GEDI canopy metrics

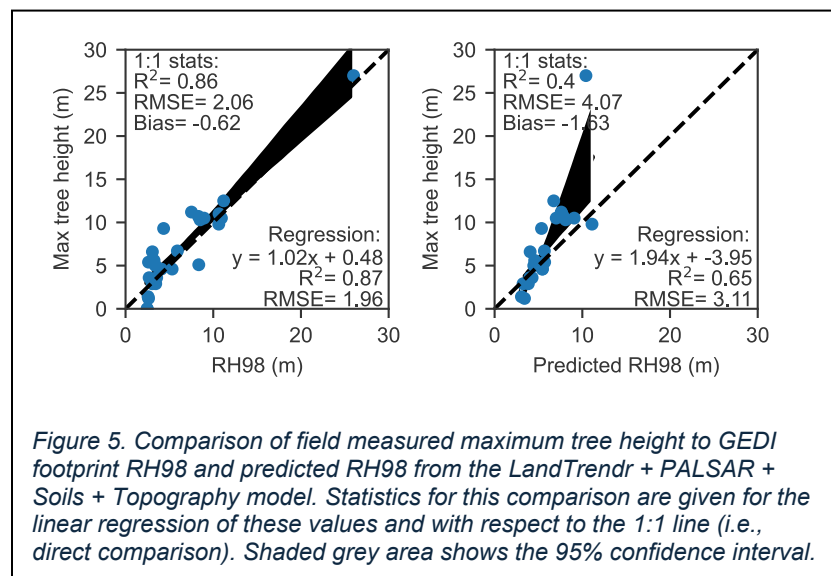
Random forest models of the GEDI canopy metrics had similar accuracy statistics between predictor sets using the same combination of sensor types despite using more complex processing (i.e.,

CCDC versus LandTrendr) or more observations (i.e., HLS versus L30) (Figure 3). For example, models using optical data sources alone (LandTrendr, CCDC^{L30}, CCDC^{HLS}) had an RMSE that differed at most 2.6% from the mean RMSE across the set of models for the same metric. The model RMSEs were nearly the same for CCDC^{HLS} and for CCDC^{L30}, as were the CCDC fit RMSEs for each band with mean differences of 1.28e-3 for blue, 8.84e-4 for green, 2.47e-4 for red, 7.74e-4 for NIR, 1.34e-3 for SWIR1, and 1.37e-3 for SWIR2. Combining predictors from different types of data sources yielded greater improvement in models. For example, supplementing optical predictors with PALSAR reduced RMSE an average of 4.7%, and adding both PALSAR and soils and topography predictors reduced RMSE an average of 7.0%. Models using only optical predictors had higher performance than the SAR-only models. For example, the LandTrendr model explained 11.8%, 14.8%, and 8.7% more variance in cover, RH98, and FHD, respectively, than the PALSAR model.

Leave-one-year-out temporal cross-validation statistics (TCV) were very similar to the out-of-bag model statistics (OOB) using data from all years (Figure 3). TCV R^2 was lower than the corresponding OOB R^2 by 0.02 on average, and TCV RMSE was lower than OOB RMSE by 4.8% on average. While TCV bias appears to be significantly higher than OOB bias (Figure 3), both TCV bias and OOB bias were still close to zero across all models. Bias as a percentage of the mean observed value was at most 3.3% for the OOB models (LandTrendr Cover model) and 4.6% for TCV models (CCDC^{L30} + PALSAR Cover model).

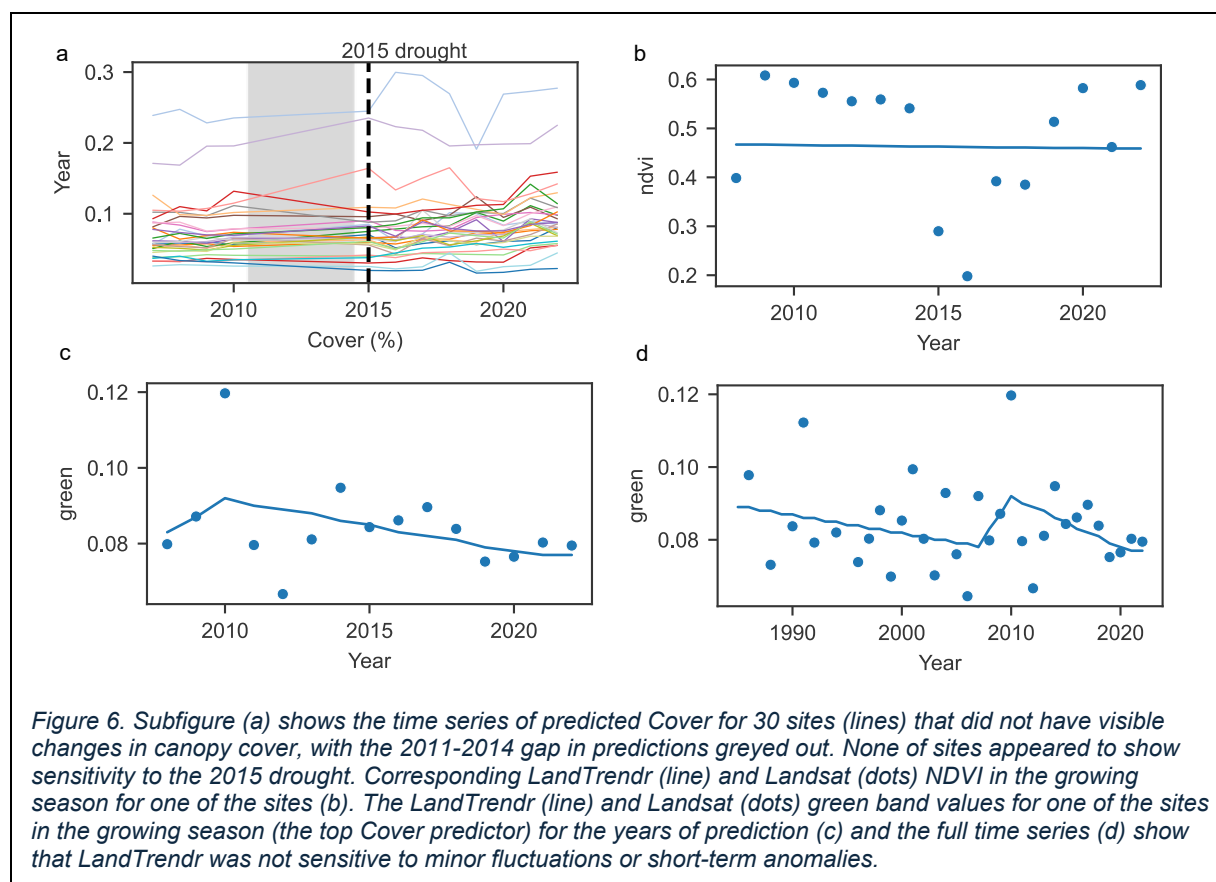


The models using the LandTrendr + PALSAR + Soils + Topography predictor set (Figure 4) were chosen for mapping canopy structure across time because they had nearly the same accuracy as the most accurate models but were substantially less complex. These models using LandTrendr had RMSE values that were higher by only 0.07% for Cover, 0.04 m for RH98 and 0.003 for FHD in comparison to the most accurate models that instead used the CCDC^{L30} or CCDC^{HLS} predictor sets with 54 more variables. The residuals of the chosen models were significantly different ($\alpha=0.05$) from the best models in paired Wilcoxon signed-rank tests (Table S 1), but even very small differences could be significant because of the large sample size ($n=277,046$). Although the models had near zero bias overall, there was substantial bias within particular ranges of observed values, reflecting the compression towards the mean that is common for random forest and other machine learning models (Zhang and Lu, 2012). The Cover model tended to overestimate the abundant low cover values, with an observed cover of <1% being predicted as 10.4% on average, and the rarer cover values over 50% were underestimated by 27.2% cover on average. This compression towards the mean was also present for FHD but was less extreme for RH98. We attempted to reduce this effect by using the first bias-correction method (BC1) in Zhang & Lu (2012). However, the accuracy statistics and distribution of predictions from the bias-correction were virtually identical to the original model (Appendix 1.1), and, therefore, the original model was used for all subsequent analysis for simplicity.



The compression towards the mean of predicted RH98 was also apparent when compared to field observations of maximum tree height within GEDI footprints (Figure 5). The regression of predicted RH98 on field maximum tree height had a slope of 1.94, but this was largely due to the leverage of a single tall tree. Without this observation, the linear regression became closer to 1:1 with a slope of 1.41 and intercept of -1.35, and the direct RMSE (i.e., not of the linear regression) dropped to 2.3 m. The GEDI footprint RH98 values corresponded closely with the field measured maximum tree heights, having a slope close to 1, intercept close to 0, and RMSE of 2 m.

Models were, however, resilient to anomalous conditions like the 2015-2016 drought. There was no substantial decrease in predicted Cover in 2015 or 2016 for the 30 sites that had no visible real changes in canopy cover when checked with very high resolution imagery (Figure 6a). The LandTrendr values for bands and metrics that would be sensitive to drought, like NDVI, were fit through anomalous changes in the spectral time series (Figure 6b). Also, bands with high level of importance in the models, like the green band in wet season for Cover, often did not even show significant changes in spectral values corresponding to the drought (Figure 6c). LandTrendr was fit to the full 1984 to 2022 time series and thus was less sensitive to relatively minor or short-term variations (Figure 6d).



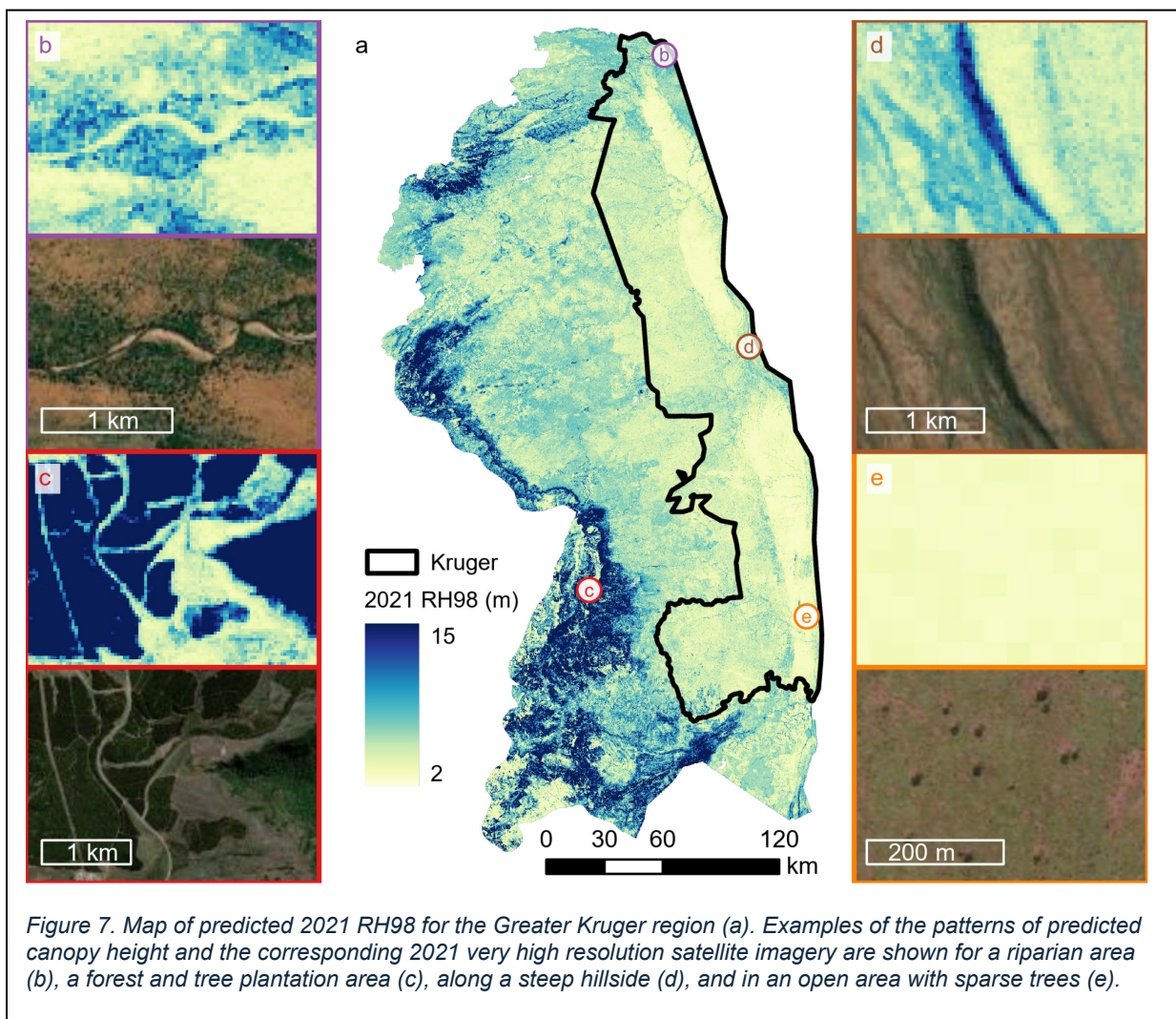
The mixed effects models used in model-based estimation for each metric were fit to the sample of 1124 GEDI observations and random forest model predictions in the 11 area-year combinations (i.e., domains). Across domains there was a minimum of 2, maximum of 299, and mean of 102 sample units. In our comparison to models with alternative random effects structures, we found models using the combined Area:Time random effect had the lowest AIC for the RH98 and FHD metrics, while the model with only an Area random effect had the lowest AIC for the Cover metric.

4.2 Maps of canopy structure and change for impact areas

Maps of GEDI Cover, RH98, and FHD were created from models using the LandTrendr + PALSAR + Soils + Topography predictor set and used to quantify canopy structure before and after change events in areas known to have undergone elephant impacts, timber harvesting, fuelwood harvesting, and woody encroachment between 2007 and 2022, when PALSAR-1 & 2 annual mosaics were available. These maps are publicly available on the Oak Ridge National Laboratory DAAC

(<https://doi.org/10.3334/ORNLDAAAC/2401>). The map of 2021 RH98 reflected the broader patterns of

canopy height known in the region (Figure 7a). It shows low canopy heights in the eastern half of Kruger National Park on the nutrient rich basaltic soils which are primarily grasslands with sparse trees, while canopy height tends to be greater on the nutrient poor granitic soils in the western half of the park which supports more trees and shrubs. Predicted RH98 is also higher where taller trees are known to exist such as in riparian areas (Figure 7b), along steep hillsides (Figure 7d), and especially in the western forests and tree plantations (Figure 7c). However, the height of large individual trees and small tree patches in sparse savanna areas were often underestimated (Figure 7e), and tree height in areas of grasslands and low shrubs were overestimated as 2-3 m.



4.2.1 Elephant Impacts in Thornybush Reserve

The map of canopy cover change in Thornybush Reserve from 2017, when eastern fences with adjacent reserves were removed, to 2021 shows a distinct decline within the property boundaries (Figure 8a). There are slight increases in cover in communal lands to the west and south where fences still exist. The decrease in canopy cover exceeded 20% in some areas (Figure 8c & d). Note that the maps of change such as in Figure 8a and visualization of high resolution imagery such as Figure 8c-d are for illustration and that the change in the case study areas was formally assessed through small area estimation using the maps before and after the change event as described in section 3.3 and shown in Figure 8b. Mean predicted canopy cover for the reserve declined from $12.2 \pm 1.4\%$ in 2017 to $8.9 \pm 0.7\%$ in 2021 (Figure 8b). Predicted RH98 and FHD showed less dramatic declines but also had relatively smaller 90% confidence intervals such that the change could still be deemed significant.

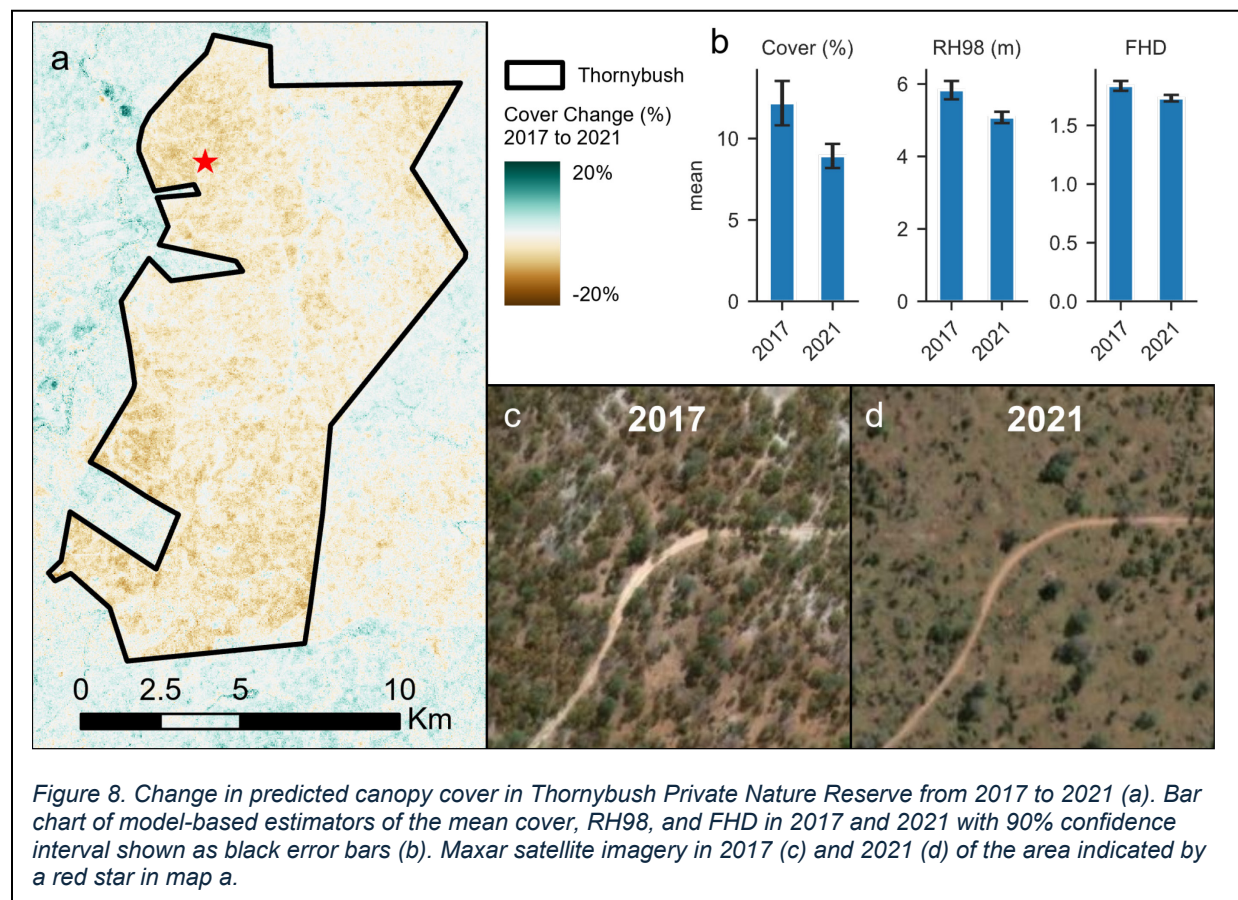
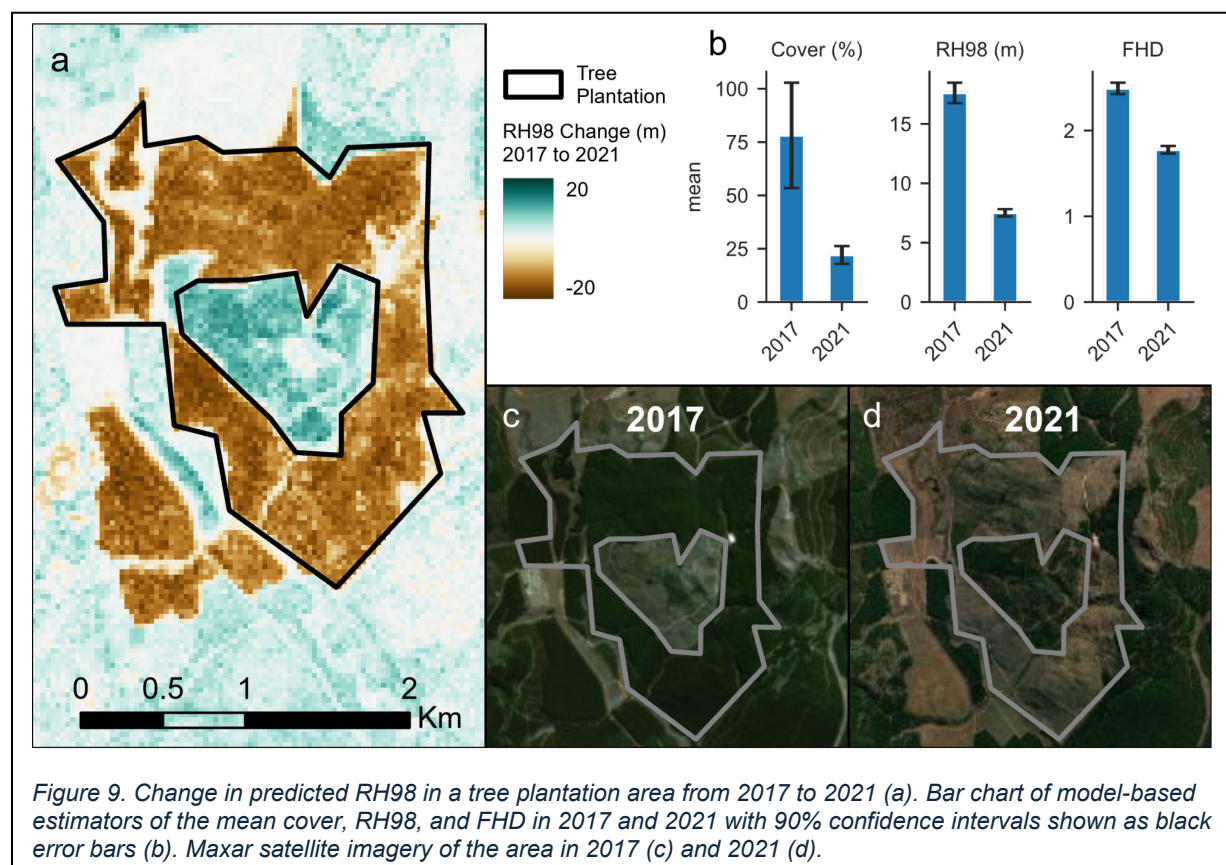


Figure 8. Change in predicted canopy cover in Thornybush Private Nature Reserve from 2017 to 2021 (a). Bar chart of model-based estimators of the mean cover, RH98, and FHD in 2017 and 2021 with 90% confidence interval shown as black error bars (b). Maxar satellite imagery in 2017 (c) and 2021 (d) of the area indicated by a red star in map a.

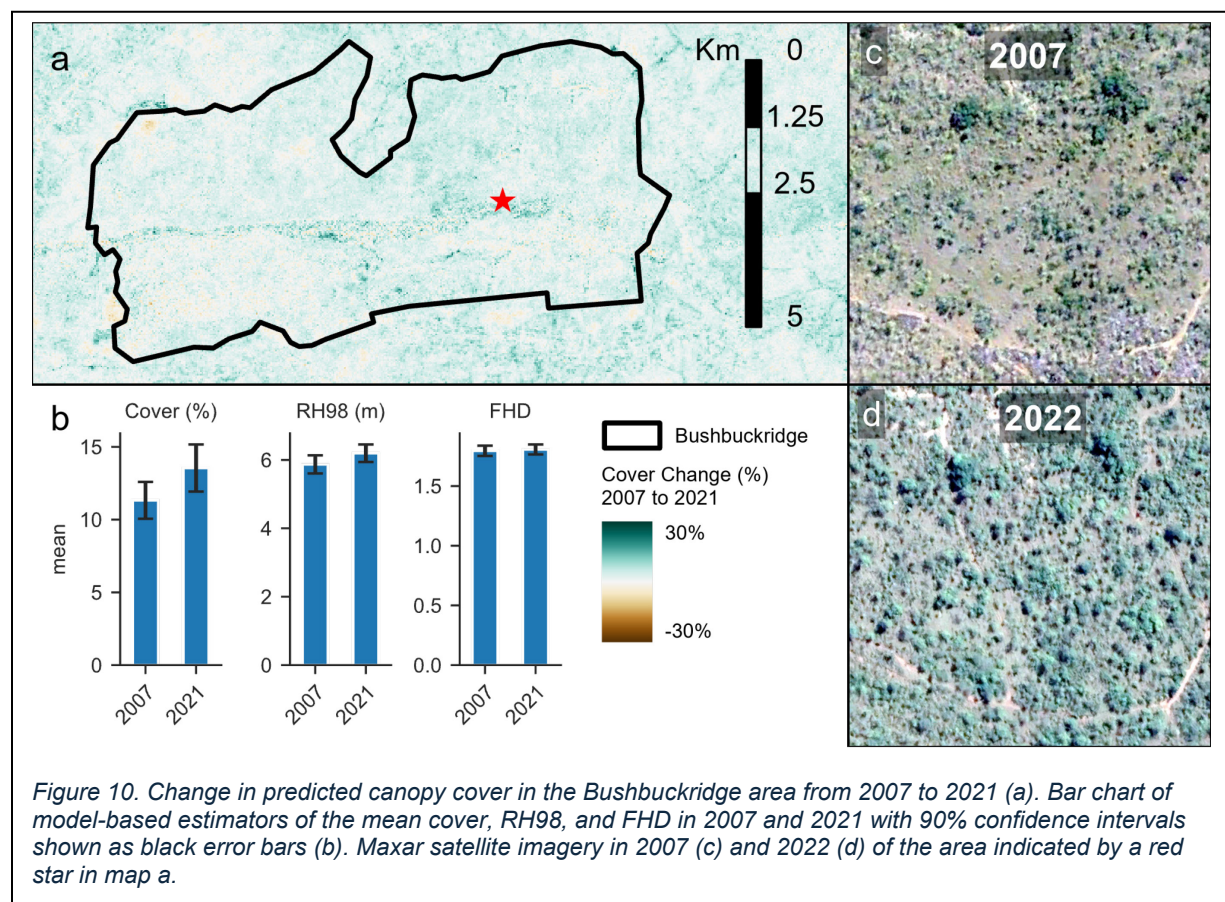
4.2.2 Timber harvesting in tree plantations

Figure 9 illustrates the predicted 2017-2021 change in RH98 for a harvested patch within the region of tree plantations in southwestern portion of the Greater Kruger area. The pattern of RH98 change corresponds with the changes visible in Maxar imagery for the same time period (Figure 9c & d). Although the delineated area appears to contain some small patches of remaining trees post-harvest, estimates of the mean for all metrics in 2021 was higher than would be expected given that most of the area appears to be clear cut (Figure 9b). Mean cover also appears to be lower than what's visible in the imagery in 2017 (Figure 9c). With the exception of Cover in 2017, the confidence intervals for each metric are relatively small due to the low variance in the mapped values for each year, but this indication of uncertainty does not include error of the GEDI measurements themselves or the possibility of bias in specific areas or time periods.



4.2.3 Fuelwood harvesting in Bushbuckridge

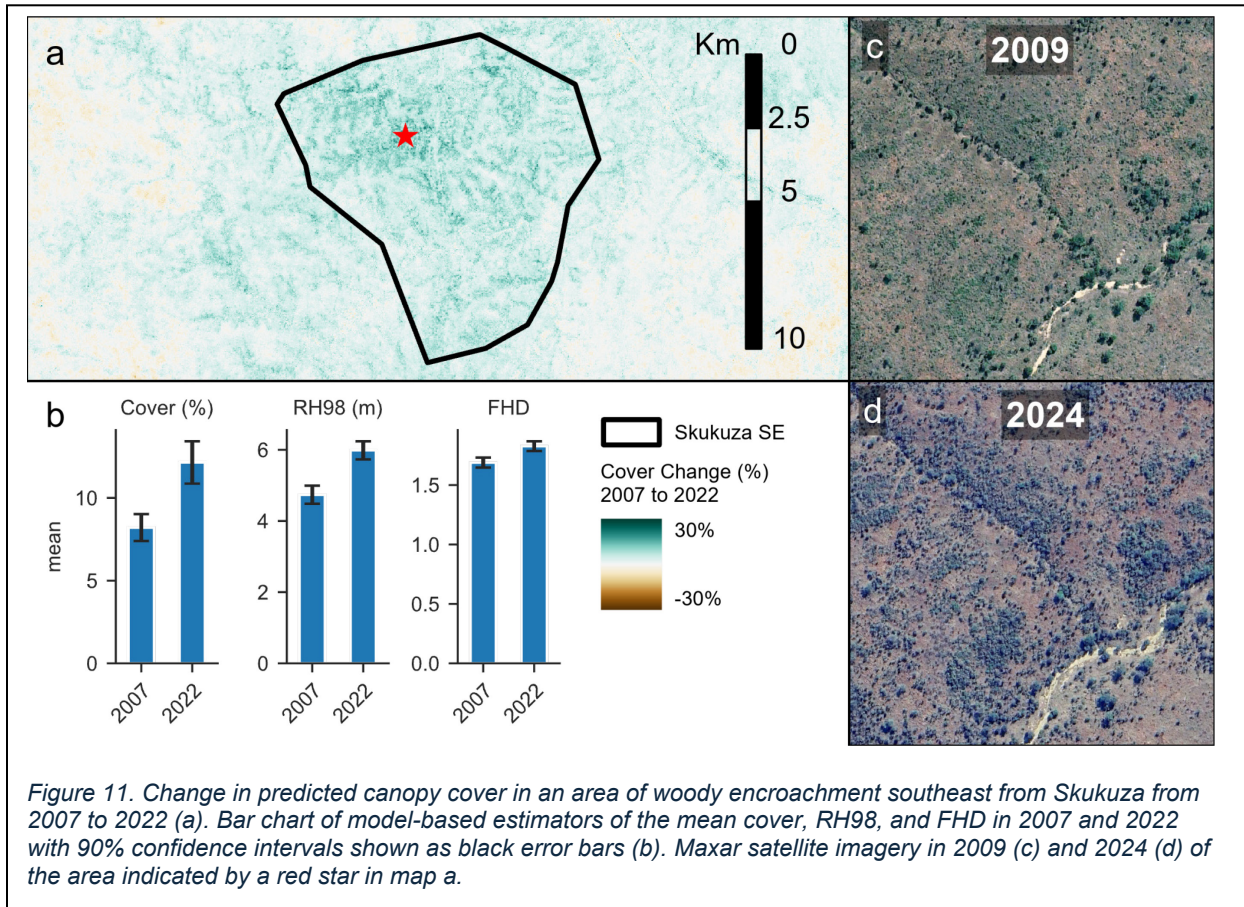
The Bushbuckridge communal lands showed an increase in canopy cover from 2007 to 2021, as did the surrounding landscape (Figure 10a). The predicted increase in cover from $11.3 \pm 1.3\%$ in 2007 to $13.5 \pm 1.6\%$ in 2021 was not significant at the 90% confidence level (Figure 10b). However, there were notable changes in specific areas such as near the riparian zone that runs east to west. The pattern of increase in cover in these areas was captured by the change map and can be seen in very high-resolution satellite imagery (Figure 10c & d). Changes in RH98 and FHD were relatively less than that of canopy cover and also not significant.



4.2.4 Woody encroachment near Skukuza

The delineated area to the southeast of Skukuza experienced noticeable woody encroachment of shrubs between 2009 and 2024 (Figure 11c and d), as have many other parts of Greater Kruger on granitic soils. This encroachment was reflected in the map of change in canopy cover between 2007 and

2022 (Figure 11a). The mean cover increased from $8.2 \pm 0.8\%$ in 2007 to $12.1 \pm 1.3\%$ in 2022. Increases in cover appeared to be greater near drainages. There was also a significant increase in RH98 from 4.7 ± 0.3 m in 2007 to 6.0 ± 0.3 m in 2022 and in FHD from 1.69 ± 0.04 in 2007 to 1.83 ± 0.04 in 2022.



5 Discussion

Our results show that fusion of moderate resolution sensors can capture canopy structure as estimated by GEDI for adequately mapping vegetation spatial patterns across a wide range of land cover and vegetation types in an African region dominated by savanna. The best performing models using a combination of moderate resolution sensors were able to explain 56%, 65%, and 50% of the variation in canopy cover, RH98, and foliage height diversity, respectively. Studies extending airborne lidar-derived woody cover with moderate resolution sensors in the Kruger area have found plot sizes of 50-100 m to yield the best trade-off in resolution and accuracy (Mathieu et al., 2013; Urbazaev et al., 2015), with the best model RMSEs ranging from 6.7% to 13.4% and R^2 from 0.71 to 0.85 (Mathieu et al., 2013; Naidoo et

al., 2016; Urban et al., 2020; Urbazaev et al., 2015; Wessels et al., 2023). Studies using higher resolutions of 15-30 m had RMSEs of 15.8% to ~19% and R^2 of ~0.24 to 0.5 for woody cover, which is a closer comparison to this study given GEDI's 25 m footprints (Mathieu et al., 2013; Urban et al., 2020; Urbazaev et al., 2015). Extension of the GEDI canopy metrics with moderate resolution sensors have obtained RMSEs of 14.6% for cover and 0.39 for FHD in North American temperate forests (Vogeler et al., 2023). We expected that the combination of GEDI's geolocation uncertainty of ~10 m (Li et al., 2023) and the high spatial heterogeneity of savannas would translate to lower accuracy when compared to similar scale ALS-based studies or GEDI extension in other forest types, but we instead found our model accuracies to be comparable.

Although the GEDI model results are on par with airborne lidar studies using similar scale, the reported model accuracies do not capture the additional error between GEDI observations and the ground conditions as determined from airborne lidar or field measurements. GEDI RH98 is known to have an RMSE of 1.64 m in African savannas (Li et al., 2023), but other canopy metrics have yet to be evaluated against airborne lidar in savannas specifically. The waveform return from spaceborne lidar may spread in areas of high slope, which makes ground differentiation difficult and further reduces canopy height accuracy for short-stature trees in particular (Gwenzi and Lefsky, 2014). Canopy metrics from GEDI footprints intersecting man-made structures may also misrepresent vegetation structure. Comparisons of GEDI cover to ALS-based cover measurements have found overall RMSEs of 10% to 21% and biases of ~0% to 11% across forest types (X. Li et al., 2024; Y. Li et al., 2024), with variations in accuracy dependent on the airborne lidar cover definition and forest type among other factors. Our comparison of GEDI RH98 with a small field dataset had an accuracy similar to that of Li et al. (2023) with an RMSE of ~2 m, and predicted RH98 had a poorer fit to field measurements (i.e., RMSE = 4.07 m) largely because of underestimation of one tall tree. We did not have access to extensive airborne lidar, and our small and opportunistically collected field data set limited our ability to rigorously test the accuracy of the other GEDI metrics in the region. Propagating errors from more extensive ground or airborne lidar measurements to GEDI to wall-to-wall maps will be particularly important for uncertainty estimation in future research in savannas because of the lower values and range of variation in canopy

structure compared to most forests, which means relative error (i.e., as a percent of the prediction) could be high compared to forests.

The comparison of different predictor sets showed that fusion of multiple types of data sources improved model performance, but that including additional optical observations (i.e., HLS vs L30) or more complex temporal processing (i.e., CCDC) offered marginal benefit. While LandTrendr and CCDC have been directly compared for disturbance detection (Cohen et al., 2018), this is the first comparison that we are aware of for mapping canopy structure attributes across time. We used the LandTrendr fusion model for subsequent analyses because it provided a simpler model with fewer variables and faster computation for an increase of <1.5% RMSE across metrics compared to CCDC fusion models. However, the stability of CCDC segmentation is more robust to the addition of new observations and can yield predictions at any date (Pasquarella et al., 2022), making it potentially a better tool for frequent monitoring. Using HLS did not improve CCDC fits for each band and the HLS-based model actually performed slightly worse than when using Landsat-only for Cover and FHD, indicating that additional observations were not needed or that the true HLS dataset which features BRDF correction may be necessary. Although the use of CCDC with HLS versus Landsat-only has not previously been compared for canopy structure modeling, data reconstruction with harmonic regression improves when there are no lengthy temporal gaps and at least seven observations per year (Pasquarella et al., 2022; Zhang et al., 2021), which may be hard to obtain in regions with cloudy wet seasons. Also, use of HLS in CCDC has improved capturing of phenology, fires, and wetland dynamics in grasslands (Zhou et al., 2019). Using Landsat as the only predictor set would enable mapping of canopy structure as early as 1985 and would be only 7% less accurate on average than the best fusion models. Another interesting contrast to previous research is that the optical-only LandTrendr model explained 12% more variance than the PALSAR model, despite the higher performance of SAR-based models for mapping canopy cover in the region (Naidoo et al., 2016). The lower performance from SAR in our case may be due to using JAXA's annual mosaics instead of careful selection of individual scenes. Use of a water cloud model or texture indices may also improve performance with SAR in savannas (Wessels et al., 2023, 2019).

Models were able to be transferred to different years with minimal impact on overall accuracy, but the compression towards the mean indicates that applying the models in areas of particularly high or low

canopy cover or height likely leads to biased estimates at the pixel level. Temporal cross-validation had slightly lower R^2 values and slightly higher RMSEs than out-of-bag accuracy with an absolute bias that was still close to zero for all canopy metrics. This test indicates that these models are unlikely to have substantial bias or changes in error from temporal transfer to years with similar conditions (Filippelli et al., 2024). However, temporal transferability was only able to be tested over 2018-2023 because of GEDI availability. Evaluating transferability over time spans encompassing a wider range of conditions, such as extremely wet or dry years, and checking model coverage of predictor ranges (Meyer and Pebesma, 2021) would improve user confidence in transferability. Examining the time series of Cover predictions (Figure 6a) showed that the model was not sensitive to the 2015-2016 drought event, likely because of LandTrendr's ability to create linear segments that ignore short-term anomalies (Figure 6b-d). The greater source of variation in accuracy was from compression towards the mean leading to overestimation of low values and underestimation of high values as is common with many modeling approaches (Zhang and Lu, 2012). The effects of this over/under-estimation were also apparent when visually comparing maps to VHR imagery.

Maps of predicted canopy structure captured the expected broader patterns of relative height or cover without any noticeable artifacts (Figure 7). However, GEDI's inability to estimate RH98 below 2.34 m results in maps that overestimate canopy height in open grasslands (Li et al., 2023), and because of the small sample of high values (Figure 2), predicted RH98 rarely exceeded 20 m even in riparian areas that often have trees over 25m. Predicted RH98 also underestimated canopy height in areas of very sparse trees or small patches (Figure 7e), which may be a fundamental limitation of the scale of observation (Woodcock and Strahler, 1987). Use of higher spatial resolution imagery with a frequent return, such as PlanetScope or Sentinel-2, may be able to better capture the spatial heterogeneity of tree height and cover in savannas for monitoring (Back et al., 2025).

The direction of changes observed in the case study areas were in line with prior expectations, but the degree of change seen in maps or through model-based estimation indicate that improvements need to be made for better quantifying changes. This can be most clearly seen in the tree plantation example where mean cover decreases from 78% to 22% (Figure 9b) even though cover appears to be <15% post-harvest in the imagery (Figure 9c and d). The magnitude of change is less apparent in the imagery for the

other case study areas. Repeat airborne lidar would be a more effective means of assessing the accuracy of change, but it is rarely available. Instead, we make comparisons to VHR imagery and existing research on the same or similar areas. Mean predicted canopy cover in Thornybush declined by 3.2% from 2017 when fences were removed to 2021 (Figure 8b), with decreases exceeding 20% in some areas. Field-based studies of other private nature reserves in the Kruger area have observed even greater elephant impacts following fence removal. The Sabi Sand Wildtuin-MalaMala complex removed fences with KNP in 1993 and witnessed a 17-fold increase in elephant populations, which resulted in a ~60% decrease in total tree density between 1992 to 2011 (de Boer et al., 2015). They also observed the sharpest decline in large trees, with a decrease of 261 trees ha⁻¹ in the first five years after fence removal for trees >5 m tall (de Boer et al., 2015). By contrast, predicted RH98 declined by only 0.8 m from 2017 to 2021 in Thornybush (Figure 8b), even though VHR imagery would suggest a more substantial decline in the number of large trees in many areas (Figure 8c and d). Other instances of fence removal or reintroduction of elephants have similarly resulted in rapid reductions in large trees preferred by elephants, such as marula (*Sclerocarya birrea*) (Cook et al., 2017; O'Connor, 2017), and overall reductions in tree species richness, density of tall trees, and total basal area, particularly in riparian areas (O'Connor and Page, 2014). However, NDVI from AVHRR actually increased for private reserves in the Kruger area following fence removal (Linden et al., 2022), possibly due to increased greenness from woody encroachment of shrubs overriding tree losses. The relatively low overall decline in canopy height and cover we observed in Thornybush may be due in part to the underestimation of high canopy values prior to fence removal and overestimation of low canopy values following fence removal. This effect was also seen in the plantation harvest case study area (Figure 9), which was still showing a mean RH98 of 7.5 m post-harvest. Also, in very low tree density savannas, canopy height was effectively smoothed out by the moderate resolution sensors (Figure 7e), which means that residual large trees may be difficult to detect in areas where density has been reduced substantially, like in some parts of Thornybush.

There have been conflicting reports on the sustainability of fuelwood harvesting in the Bushbuckridge municipality of South Africa and its impact on vegetation structure (Shackleton et al., 2022, Table 2). Our analysis of canopy structure change in a Bushbuckridge communal rangeland showed a non-significant increase of 2.2% in cover and even less substantial relative changes in RH98 and FHD (Figure 10).

These changes are in line with coppice growth from fuelwood harvesting (Twine and Holdo, 2016), but repeat lidar surveys of nearly the same area of Bushbuckridge show an even greater compensatory regrowth and bush thickening between 2008 and 2012, with a greater than 1 m increase in height for 21.1% of trees and an increase in estimated biomass of 11.34 Mg ha⁻¹ (Mograbi et al., 2019, 2015). However, our maps also showed an increase in cover across much of the surrounding area (Figure 10a), suggesting the changes could alternatively be from either global causes of woody encroachment such as CO₂ enrichment (Stevens et al., 2016), regrowth from decreases in fuelwood consumption if alternative energy sources were adopted in later years (Twine and Holdo, 2016), or simply error in the maps. Although the changes in the canopy structure maps were corroborated with VHR imagery in some areas (Figure 10c and d), either higher precision remote sensing models or a greater degree of change will be necessary to detect that a significant change has occurred from fuelwood harvesting.

The change in canopy cover from woody encroachment was indeed detectable in other areas that had a greater magnitude of change. The area to the southeast of Skukuza had a mean increase in cover of 3.9% over 15 years, or 0.26% per year on average. Another study estimated woody encroachment in the southwestern portion of KNP using a Landsat-based model calibrated from 35 field plots and found an increase in the area of woody plants from 3.4% in 1992 to 10% in 2022, which is 0.22% per year on average (Maphanga et al., 2024). While overall woody plant cover is known to be increasing, the increase is occurring primarily in shrubs and short-stature trees like *Dichrostachys cinerea* and *Combretum apiculatum*, while larger trees like *Acacia nigrescens* and *Sclerocarya birrea* are decreasing in density (Zhou et al., 2021). We predicted an increase in canopy height in the Skukuza case study area, which could reflect the increasing area of short-stature trees. We also did not see any substantial reduction in large trees in VHR imagery for this area, as is happening primarily in areas closer to perennial water where elephants frequent.

6 Conclusion

The results of this study demonstrate that extension of GEDI canopy metrics through a combination of moderate resolution sensors can capture the broad patterns of canopy structure and changes in an African savanna, even when extrapolating temporally. Given that studies using airborne lidar data as a reference source yield similar accuracy when modeling at similar scales (i.e., 15-30 m), space-borne lidar

presents an appealing alternative reference source for wall-to-wall mapping of canopy structure in savannas that is available globally with greater frequency. However, both the model results and maps revealed an overestimation of low values and underestimation of high values that likely resulted in biased estimators for specific areas and muted estimates of change. Improving model accuracy at the distribution's extremes and propagating uncertainty will be crucial for advancing this approach from monitoring the direction and relative intensity of changes to reliably quantifying changes. Despite these remaining challenges, being able to map canopy structure and vegetation change over vast savanna landscapes with this approach will enable research applications that are typically confined to smaller scales or sample sizes. For example, ecologists may use these maps to examine differences in structure between vegetation types, and the maps could be included in models of wildlife occupancy and movement patterns. Time series maps of canopy structure will also allow land managers to monitor for significant changes occurring from pressures such as increasing elephant populations, illegal timber harvesting, fuelwood harvesting, and woody encroachment. Advancing regular monitoring of savanna vegetation will thus enable the adaptive management strategies being implemented in Kruger National Park and support policy making for the Greater Kruger region.

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CHAPTER 2—Remote sensing of tree canopy cover reference sources for post-stratified estimation of forest area and aboveground biomass

1 Abstract

Tree canopy cover is measured using diverse field and remote sensing techniques that differ in definition, bias, cost, and availability, creating challenges for consistent large-area and multi-temporal mapping. These differences also raise questions about how reference data selection influences downstream applications such as post-stratified estimation of forest attributes. This study evaluates how alternative canopy cover reference sources affect canopy cover mapping accuracy and the precision of post-stratified estimators of forest area and aboveground biomass. We developed random forest models to map canopy cover across Colorado using temporally fitted Landsat time series (LandTrendr) and topographic predictors, trained with multiple field-, aerial-, and lidar-based cover reference sources, including selected combinations. Canopy cover maps were evaluated using model performance metrics, comparison with airborne lidar canopy cover maps, and their performance as post-stratification layers for Forest Inventory and Analysis (FIA) estimation at state and county scales and within major forest types.

Landsat model performance was similar across most reference sources ($R^2 = 0.70\text{--}0.90$; RMSE = 7–12%), as was map accuracy relative to airborne lidar ($R^2 = 0.74\text{--}0.84$; RMSE = 9–12%), except for GEDI-derived cover, which performed substantially worse. The relative efficiency (RE) of statewide estimators (i.e., variance as compared to using a simple random sample) varied modestly among the cover sources for aboveground biomass (RE = 1.21–1.42) and more strongly for forest area (RE = 1.59–3.25). Relationships between map accuracy and RE were weak ($|r| \leq 0.3$ when excluding GEDI), whereas RE was strongly related to the plot-level correlation between canopy cover and the target variable ($r = 0.94$ for biomass; $r = 0.45$ for forest area). Combining reference sources increased spatial and temporal coverage without degrading map accuracy and occasionally improved estimator precision. These findings indicate that stratification effectiveness depends more on the functional linkage between auxiliary data and forest attributes than on marginal improvements in canopy cover map accuracy alone.

2 Introduction

The tree canopy cover of a forest stand is a function of other underlying aspects of stand structure such as aboveground biomass, basal area, and volume. Because of this, canopy cover can serve as a more easily measured proxy to these structure variables, particularly through the use of remote sensing (Jennings et al., 1999; Van Laar and Akça, 2007). However, canopy cover may be measured through a wide range of ground and remote sensing techniques that are based on different functional definitions of cover and have differences in measurement error or biases. These differences may pose a challenge for comparing or combining canopy cover datasets and selecting an appropriate canopy cover measurement technique, but this has yet to be tested. Choosing the optimal cover dataset or measurement method likely depends on the specific application, such as estimating other forest structure attributes or characterizing wildlife habitat.

Canopy cover, also called crown cover, is most commonly defined as the percent of a horizontal ground area covered by the vertical projection of tree crowns *including* internal canopy gaps (Jennings et al., 1999; Tang et al., 2019). However, some measurement methods for canopy cover may functionally represent a cross between this definition and alternative definitions like “effective canopy cover”, the percent of horizontal ground area covered by the vertical projection of tree canopy elements *excluding* internal canopy gaps (Rautiainen et al., 2005; Tang et al., 2019), or “canopy closure”, the percent of the sky covered by tree crowns when viewed from a single point (Jennings et al., 1999). Field measurements by point intercept, line intercept, crown area mapping, and ground profiling lidar may most closely match the standard definition of canopy cover because they are nearly vertical measures and internal canopy gaps can be filled (Korhonen et al., 2006). Use of hemispherical photography, spherical densiometers, and terrestrial laser scanning include off-zenith measurements and may include internal canopy gaps, even when averaged over multiple points and limiting off-zenith angles (Paletto and Tosi, 2009; Tang et al., 2019). Direct measurements of canopy cover from high resolution remote sensing also typically include off-nadir angles and internal canopy gaps. Aerial photo-interpretation of a dot-grid or crown delineation and calculating the discrete lidar percent of first returns above a given height threshold are the most common remote sensing methods for measuring canopy cover either directly or through manual interpretation (Avery, 1978; Korhonen et al., 2011). Large footprint waveform lidar also provides a direct

measurement of “effective canopy cover” by taking the fraction of return energy above the ground while accounting for ground and canopy reflectance, such as in the L2B “cover” metric from the space-borne Global Ecosystem Dynamics Instrument (GEDI) (Tang and Armston, 2019).

This diversity in canopy cover measurement techniques and corresponding datasets poses a challenge for consistent cover mapping with remote sensing across wide spatial and temporal expanses. Canopy cover reference data has limited spatiotemporal availability and can be costly or sometimes impossible to collect for every time period or location of interest. Combining data sources, either in model development or through their derived maps, may alleviate some of these data restrictions. However, the differing biases and precisions of various measurement techniques makes their combination suspect without further evaluation. Previous research has primarily focused on directly comparing the interrelatedness of measurement techniques (Bunnell and Vales, 1990; Fiala et al., 2006; Ko et al., 2009; Korhonen et al., 2011, 2006; Paletto and Tosi, 2009; Riemann et al., 2016; Smith et al., 2009; Tang et al., 2019). However, it is still uncertain whether the differences between techniques translate into substantial differences in map accuracies or impacts on downstream applications.

The complications of selecting and combining different reference sources for canopy cover mapping are especially pertinent for applications in forest inventories and monitoring programs. One example is the importance of canopy cover maps in defining and identifying forest land, such as the use of a 10% cover threshold in the Food and Agriculture Organization’s definition of forest for their global assessments (FAO, 2020). Consistent measurement and definition of canopy cover affect forest area estimates and thus have subsequent implications for carbon monitoring, such as for Assessment Reports from the Intergovernmental Panel on Climate Change (IPCC), and for distributing incentives and aid through the program for Reducing Emissions from Deforestation and forest Degradation (REDD+) in developing countries. Canopy cover maps are also essential for the estimation of related forest structure attributes. The Forest Inventory and Analysis (FIA) program of the United States relies on Landsat-based Tree Canopy Cover (TCC) maps (Coulston et al., 2012; Heyer et al., 2025) for stratifying field plots to produce post-stratified estimates of forest structure variables across areas of interest (Lister et al., 2020). The FIA post-stratified estimates get incorporated into state and national reports that span multiple years (Bechtold and Patterson, 2005).

Comparing the precisions of post-stratified estimators of forest attributes provides a means to understand the relative strengths of canopy cover maps derived from different reference sources and can be translated to direct economic value for inventory programs. The gain or loss in precision from using a map for stratification can be expressed by the relative efficiency (RE) of the estimator, which we define here as the ratio of the variance of the base estimate (V_{base}) over the variance of the estimate derived from post-stratification with a test strata map (V_{test}):

$$RE = \frac{V_{base}}{V_{test}}$$

The base estimate could be derived from a simple random sample (SRS) or post-stratified estimation with a given strata map that forms a basis for comparison such as from TCC. RE can also be interpreted as the multiplicative increase in the number of field plots necessary to achieve the same level of precision, and guidelines for meaningful levels of RE have been given as 1 = no gain, 1.2 = minimal gain, 1.5 = moderate gain, 2 = substantial gain, 4 = excellent gain (Czaplewski and Patterson, 2003). In parts of Minnesota, post-stratified estimators that used percent tree canopy cover maps for stratification yielded relative efficiencies of up to 43.61 for proportion of forest area and 1.38 for growing stock volume when compared to estimates from a simple random sample (McRoberts et al., 2014).

Although canopy cover maps can improve the precision of forest structure estimates using post-stratified estimators, collecting the necessary reference data to build and validate the maps used for stratification, can be costly and time consuming. In Colorado, the reference data used in generation of the NLCD TCC maps consists of manual photo-interpretations of canopy cover using dot-grids on aerial imagery for all 2012 & 2013 inventory year FIA plots (Coulston et al., 2012; Heyman et al., 2025). Incorporating alternative reference sources, such as airborne lidar canopy cover or even canopy height (Schroeder et al., 2022; Strunk et al., 2019) in developing maps for post-stratification would open opportunities for improved precision of forest structure estimates of the past and in coming years, without the need for additional field plots.

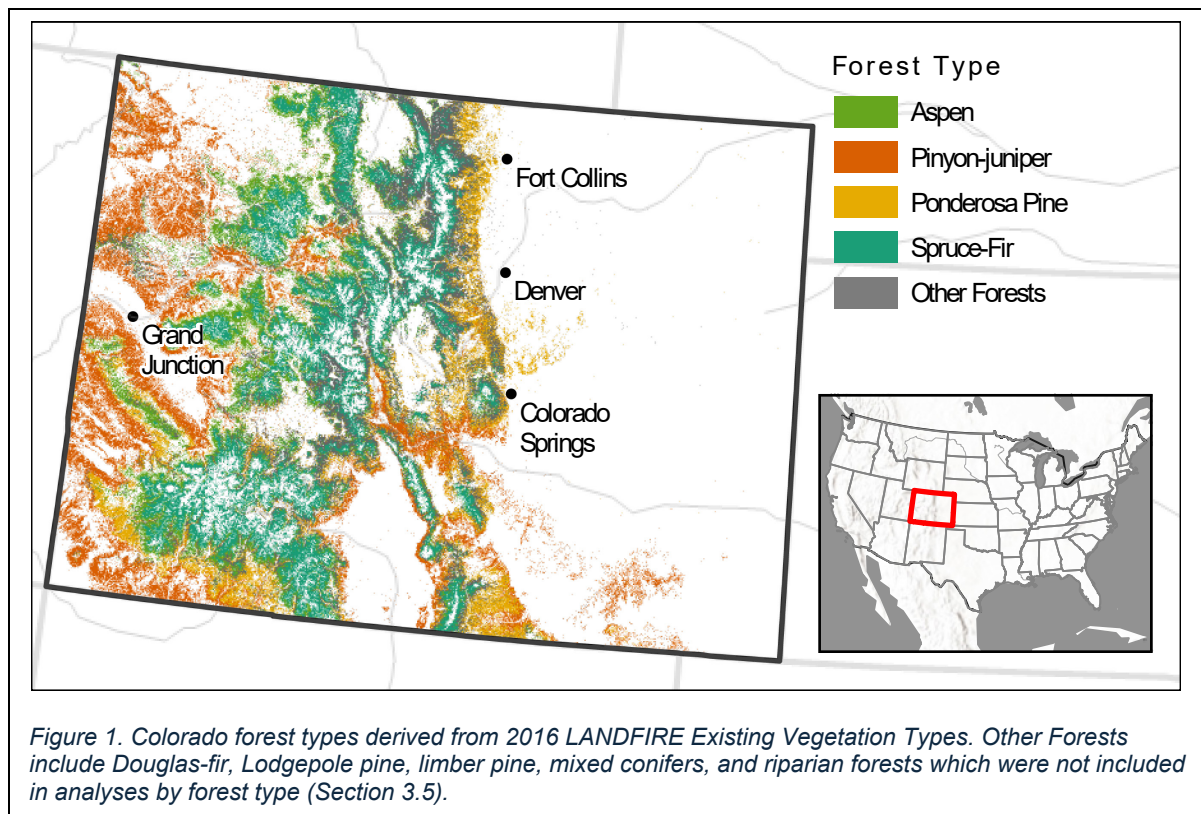
The goal of this study was to understand the impact of different canopy cover reference sources on canopy cover mapping accuracy and the subsequent effect of these maps on the precision of post-stratified estimators of forest structure. We also sought to understand how the precision of forest structure estimators varied across different forest types depending on the cover map used in post-stratification. To

address these goals, we first produced Landsat-based maps of canopy cover using several different canopy cover references sources, which were then used for post-stratified estimation of aboveground biomass and forest area. We compared the precision of these estimators at the state-level and county-level and across forest types in Colorado. Through these comparisons we were able to identify which references sources led to the greatest efficiency gains, and we discuss their trade-offs given their associated cost and difficulty of collection.

3 Methods

3.1 Study Area

Colorado, USA (~270 km²) contains diverse topographic and climatic regions which create a wide range of forest types and structure characteristics throughout the state (Figure 1). The canyons and mesas of the Colorado Plateau make up the western third of the state, and short stature pinyon-juniper woodlands with low tree cover are common in the arid lower elevations of this region. Pinyon-juniper woodlands make up 28.3% of forested land in the state (USDA Forest Service, 2023). The central third of the state is comprised of the southern Rocky Mountains, which receives greater precipitation and has vegetation types that vary by elevation and with historic disturbance patterns. Montane forest type groups at moderate elevation ranges are dominated by aspen (15.3%), ponderosa pine (6.3%), and Douglas-fir (6.7%), and forests at higher elevations are dominated by lodgepole pine forest (6.2%) and spruce-fir forests (20.8%) in the subalpine (USDA Forest Service, 2023). The Great Plains makes up the eastern portion of the state and is composed mostly of shortgrass prairie and agricultural land with riparian areas dominated by cottonwoods (0.5%) as the main forest type (USDA Forest Service, 2023).



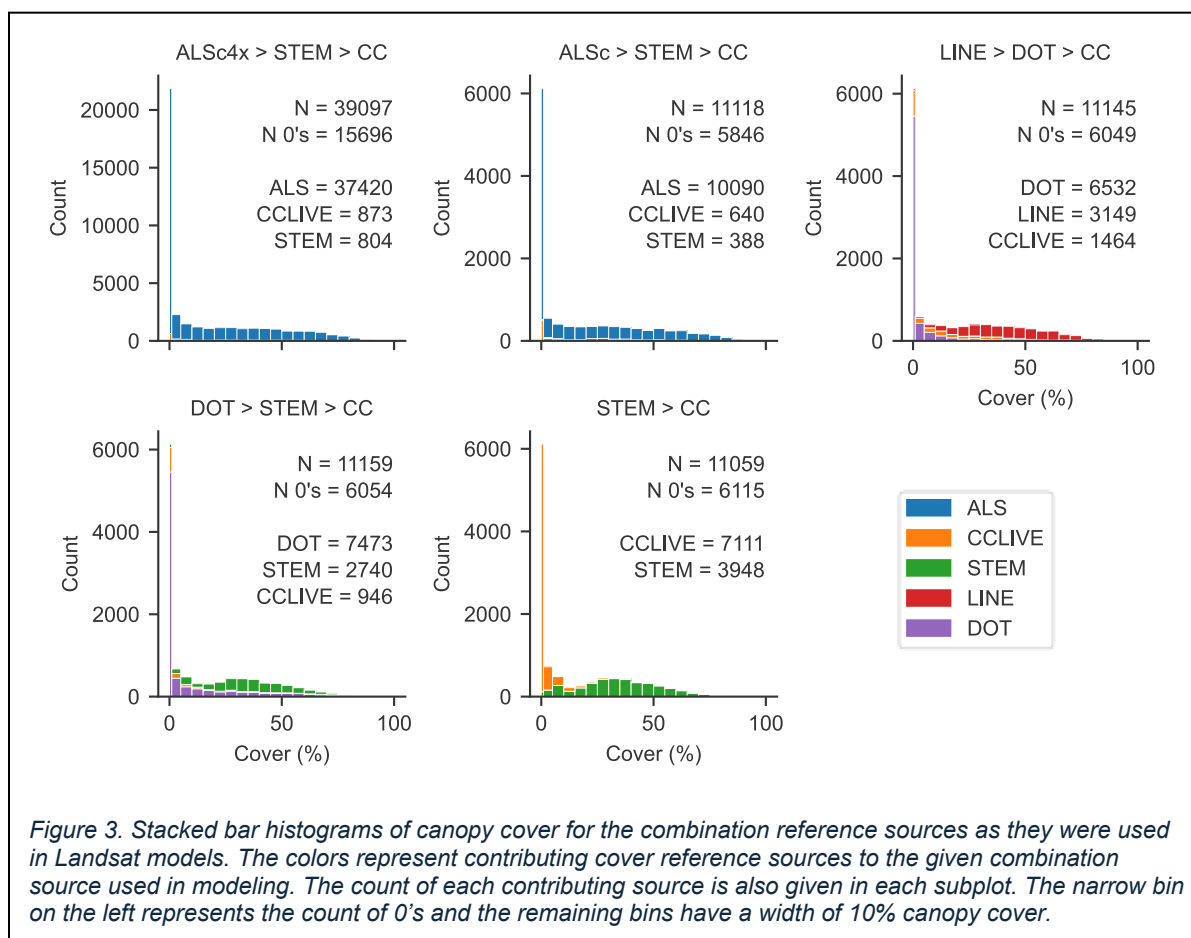
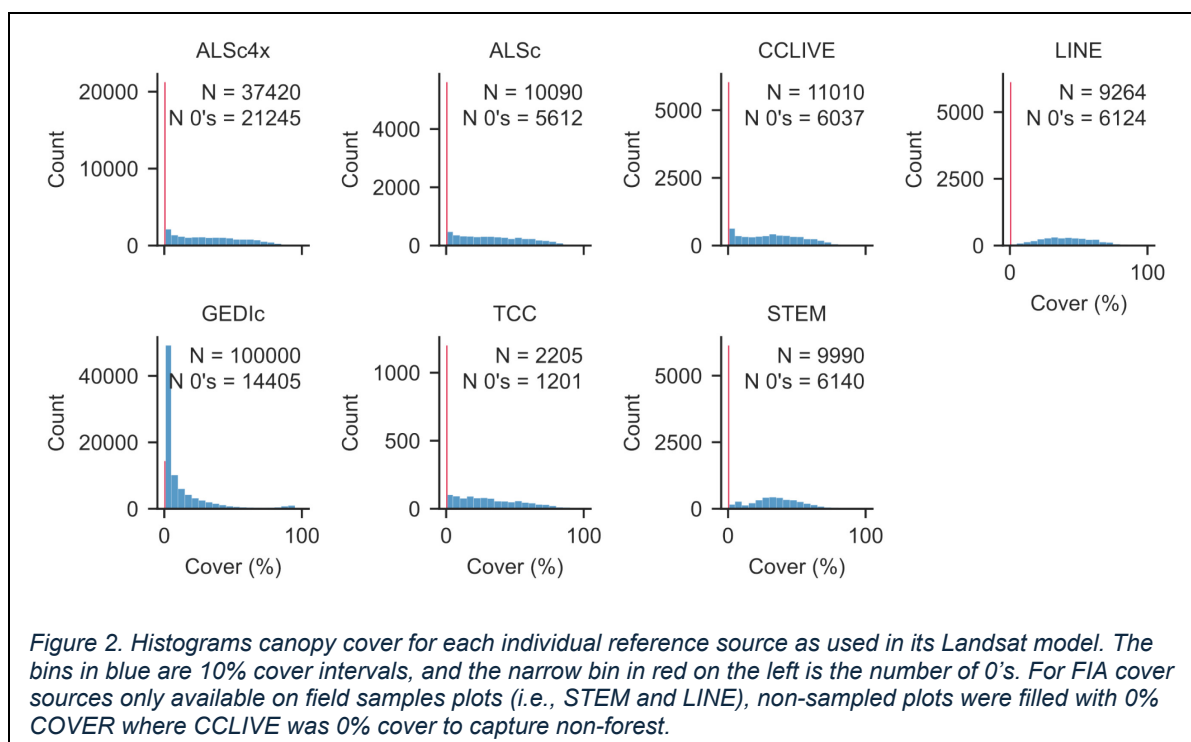
3.2 Reference sources

We prepared reference data on canopy cover from six field and remote sensing sources, which are defined and described in the following subsections and listed in Table 1. The reference sample for all datasets, aside from spaceborne lidar, was obtained from FIA field plot data or extraction of remotely sensed variables over true FIA plot locations. FIA uses a systematic sampling frame with one plot in each 24 km² cell of a hexagonal grid system covering the US (Bechtold and Patterson, 2005). The cells of the hexagonal grid in Colorado are divided into 5 panels and up to 2 subpanels, where ideally all cells in a panel or subpanel are visited for field collection in a given year. Additional plots may be present in certain areas, but in this study, we only used plots from the single intensity sample distribution. This allows the plots to be treated as part of an equal probability simple random sample for population estimation (Bechtold and Patterson, 2005). Colorado contains 11,226 single intensity plots and is on a 10-year cycle such that approximately 10% of all plots are visited each year from a different subpanel. The sample for the 2019 evaluation year (i.e., EVALID=08901) was used for post-stratified estimation, but the model training sample varies for each data source due to the availability of measurements (Figure 2), which is

described in more detail in the following sections. Training data distributions were also different between combination sources (Figure 3). For model calibration and validation, we only used a single measurement across time for each FIA plot, starting with plots from inventory year 2009 and selecting the measurement from the most recent inventory year when multiple measurements were available. This was done because using measurements of the same plot at multiple times in model validation could bias accuracy statistics because of temporal autocorrelation (Roberts et al., 2017).

Table 1. Summary table of reference data sources of canopy cover used in this Colorado study.

Name	Data source	Description
TCC	FIA nationwide special study	Derived from photo-interpretation of NAIP aerial imagery with a dot-grid covering FIA plots from inventory year 2012 and 2013 in Colorado. Collected to enable the creation of the NLCD TCC product as part of an FIA special study.
DOT	FIA pre-field data	Derived from photo-interpretation of NAIP aerial imagery with a dot-grid covering FIA plots. Includes all data from TCC described above, and ~700 plots per year in subsequent years, which are mostly plots with zero or low canopy cover.
CCLIVE	FIA database	Mix of methods which form the LIVE_CANOPY_CVR_PCT variable in the FIA database and available for inventory plots.
STEM	FIA algorithm applied to FIA data	Calculated from mapping of tree crowns on forested FIA subplots. Species and tree stem locations were measured, and crown sizes were derived from DBH to crown allometry (Toney et al., 2009). Tree locations are no longer in the public FIA database.
LINE	FIA database	Line intercept sampling on field visited FIA plots in the Rocky Mountain region only.
ALSc	USGS 3DEP, CO Hazard Mapping, OpenTopography	Airborne lidar percent of first returns above 2 m calculated over FIA plots. ALSc4x uses a 4x intensified sample based on random selection in intensified hexagonal grid cells that do not contain an FIA plot.
GEDlc	NASA GEDI L2B v2	Spaceborne lidar above ground energy return in 25 m footprints. Not collocated with FIA plots.



3.2.1 Aerial image-based cover (*TCC* and *DOT*)

As part of special effort to support development of the National Land Cover Database (NLCD) Tree Canopy Cover (TCC) product (Coulston et al., 2012, Heyer et al., 2025), canopy cover was measured nationally on a temporal subset of all FIA plots using photo-interpretation of a dot-grid overlaid on aerial imagery (Goeking et al., 2012). The proportion of measurements from this special study that are publicly available in the FIA database varies by state, but we were able to include all available measurements in Colorado. However, the dot-grid measurement method also became part of national FIA protocols as described in the FIA pre-field guide (Forest Service, 2021). The imagery used for photo-interpretation in this special effort was National Agriculture Imagery Program (NAIP) orthomosaics with a 0.6-1 m resolution and four bands (i.e., near-infrared, red, green, blue). NAIP imagery is targeted for summer collection, though dates can vary, and would reflect canopy cover during leaf-on. The dot-grid consisted of 109 dots distributed in a 43.9 m radius circle that was centered on and encompassed the FIA field plot. FIA technicians labeled each dot as “canopy” if it fell on the canopy of a tally tree species according to protocols in the FIA pre-field guide (Forest Service, 2021). The percent tree canopy cover was calculated as the percent of dots labeled as live tally tree canopy. We used the low confidence data flag to exclude some canopy cover measurements. Low confidence is attributed to difficulty distinguishing trees from shrubs, heavy shadowing, clouds, phenology, or poor image quality on at least 25% of the plot.

We developed a Landsat-based model of canopy cover using the dot-grid measurements from the TCC special study as the sole training source (section 3.3) and refer to this sample and model as *TCC*. For *TCC*, only 2011 NAIP was used for the photo-interpretation of most inventory year 2012 and 2013 Colorado FIA plots. This yielded a representative sample of Colorado based on two field seasons worth of plots, being approximately 20% of all Colorado FIA plots. For direct comparison of reference sources (section 3.5) and when used in models that combined multiple data sources (section 3.2.7), additional dot-grid measurements collected for FIA’s pre-field survey were included. This sample, referred to as *DOT*, includes approximately 700 plots per year from 2014 to 2019 on plots with mostly low canopy cover or 0% cover (), in addition to the TCC sample of 2012-13.

3.2.2 Mixed methods ocular estimation (*CCLIVE*)

FIA field crews make in-situ assessments of canopy cover for each forest condition on a plot. A “condition” is a delineated area of the plot with homogenous land use, owner, forest type, stand-size class, regeneration status, and stand density (Burrill et al., 2024). *LIVE_CANOPY_CVR_PCT* is a condition-level variable that has valid values for nearly all Colorado plot conditions in the FIA database starting in roughly 2009 because it is an amalgamation of different measurement methods taken for plots that are visited in the field and those that are not. The method used to measure canopy cover is specific to the type of plot and other criteria, which are described in the FIA pre-field (USDA Forest Service, 2024) and field guides (USDA Forest Service, 2025) and coded in the *CANOPY_CVR_SAMPLE_METHOD_CD* variable in the database.

We calculated the area-weighted average of the canopy cover measurements on all plot conditions, called *CCLIVE* or *CC* in some figures. Only single intensity plots from 2009 and later were used for training the Landsat-based model. Of these plots, cover measurements consisted of use of a dot-grid on aerial imagery as in *TCC* (48.5%), on-the-ground ocular estimation aided by aerial imagery (45.1%), ocular estimation using only aerial imagery (5.4%), or measurement of all tree crowns in the one acre condition if canopy cover is certain to be 6% or greater and 15% or less cover (0.9% of plots). For the subset of Colorado FIA plots used in this study, we observed that many of the *CCLIVE* values derived from on-the-ground ocular estimation were the same as the line intercept method (*LINE*) values described in section 3.2.4.

3.2.3 Stem-to-crown allometry-based cover (*STEM*)

Stem-to-crown allometry by species allows canopy cover to be estimated from field measured tree diameters, which are core measurements on FIA forest plots. FIA plots are arranged as four 24 ft radius circular subplots. The diameter at breast height (DBH) and species is determined for all live tally trees, which enables crown size to be estimated from stem-to-crown allometric equations for each species. Individual estimated live tree crowns can then be mapped using the measured tree location, which allows percent live canopy cover to be estimated from the proportion of the plot covered by the mapped crown area (Toney et al., 2009). The cover of saplings is also added using a regression-based estimate, but it is less reliable, potentially leading to overestimates of plot-level cover on plots that have a

small proportion of forest conditions. This stem-map canopy cover variable (*STEM*) was calculated for all forested plots with live trees. Sampled field plots with no live trees were assumed to have a canopy cover of 0%. Plots without field measurements and with 0% cover in the *CCLIVE* dataset (n=6027) were appended as having 0% cover to the *STEM* dataset for modeling.

3.2.4 Field line intercept cover (*LINE*)

FIA field crews in the Rocky Mountain region also measure canopy cover using a line intercept method on all subplots with forest conditions (i.e., *CRCOV*PCT_RMRS in the FIA database) (USDA Forest Service, 2025). Four 25-foot transects are established which radiate from each of the subplot centers. The length of live crown intercepted along the transects is divided by the length of transects to calculate canopy cover (*LINE*). Because of the transect layout, *LINE* can overrepresent the cover that is close to the center of the plot. Where *LINE* is collected on a plot, field crews will use it to inform the recording for *CCLIVE*, sometimes copying the value directly (Rachel Simons, personal communication). Plots without crown intercept measurements and with 0% cover in the *CCLIVE* dataset (n=6057) were appended as having 0% cover to the *LINE* dataset for modeling.

3.2.5 Airborne lidar cover (*ALSc*)

Canopy cover was measured over FIA subplot areas and mapped wall-to-wall using 54 airborne lidar collections available in Colorado from 2005 to 2021. We calculated canopy cover (*ALSc*) as the percent of first returns above a height threshold of 2 m (Hopkinson and Chasmer, 2009). For the sample used in modeling canopy cover, *ALSc* values were calculated for each FIA plot using lidar points intersecting the subplot areas. We only used FIA single-intensity plots that were completely covered by lidar, had at least 200 returns, and which were collected during leaf on (i.e., June 1 to September 15). When multiple lidar collections covered a plot, the collection that was closest in time to the FIA plot inventory year was selected for developing the Landsat models, though Landsat predictors were obtained for the lidar collection year. For modeling with *ALSc*, the FIA plot grid is a convenient sampling frame that yields a design-based sample for Colorado. For direct comparison of the other reference sources to *ALSc*, the ALS cover value for a plot was selected by those closest in time to the plot measurement year

for comparing to field-measured variables (*STEM*, *LINE*, etc.) or closest to the image year used for comparison with *DOT*.

Because ALS data were available wall-to-wall for the entire state of Colorado, we were able to test performance impacts of higher density training data for model development. Sample units of *ALSc* were generated at a 4x intensity compared to the single intensity FIA sample (*ALSc4x*) by creating a hexagonal grid with cells that are one-fourth the area (600 hectares) of the FIA Phase 2 hexagonal grid cells (2400 hectares). A random sample location was assigned for all 4x intensity hexes, except for those that contained the actual FIA plot location, in which case that location was used.

We also made maps of airborne lidar canopy cover, referred to as “lidar cover”, to compare and validate the Landsat-based map predictions created from different cover reference sources (including the *ALSc*-Landsat prediction maps). Multiple studies have proven the consistency of ALS-based cover estimates and their high correspondence with rigorous field measurements of the vertical projection of canopy cover (Hopkinson and Chasmer, 2009; Korhonen et al., 2011; Smith et al., 2009; Tang et al., 2019). To support map validation of all reference sources, lidar cover was calculated for each lidar collection at a 30 m resolution and aligned to the pixel edges of Landsat-based maps of predicted canopy cover. Because these lidar cover maps were used as a basis of comparison, further measures were taken to reduce erroneous values. The percent cover of buildings in each 30 m pixel was calculated from the 2018 Microsoft US Building Footprints dataset (Microsoft, 2018) and was then subtracted from the lidar cover to reduce overestimation of tree canopy cover in pixels containing buildings, which was critical in urban areas especially. We found areas of tall crops in northeastern Colorado also led to overestimates in the ALS cover maps. To reduce this problem, we digitized crops in these locations and reclassified cover as 0% in these areas. If a lidar collection was not entirely collected during leaf-on (June 1 to September 15), we masked out pixels labeled as a forest type containing deciduous trees according to the circa 2016 LANDFIRE Existing Vegetation Type map (LANDFIRE, 2016) since it lies in the middle of the lidar collection date range. The forest types included for phenology masking were all those with a subclass containing the word “deciduous”.

3.2.6 *Spaceborne lidar cover (GEDlc)*

We also considered spaceborne lidar as an additional reference source for canopy cover mapping, because it is available at near global extents with high frequency at no additional cost of collection. The Global Ecosystem Dynamics Instrument (GEDI) is a spaceborne waveform lidar system on the International Space Station that captures the three-dimensional vegetation structure in ~25 m footprints in 8 parallel ground transects that are sampled ~600 m apart across track and ~60 m along track. We obtained the canopy cover fraction (*GEDlc*) metric from the GEDI v2 Level-2B canopy product for all footprints in Colorado. We filtered for high quality footprints (i.e., degrade flag of 0 and quality flag of 1) that were taken only from the power beams at night and had a sensitivity of at least 95%. Even after footprint filtering, it was apparent that some entire GEDI granules had very erroneous cover values such as 100% cover over bare land or 0% in wide swaths of forest. We removed these ten entire granules from the analysis. A random sample of 100,000 footprints was selected for more efficient modeling and analysis.

3.2.7 *Combinations*

We also created combined training datasets using the above reference sources to account for temporal, spatial, and data range gaps (i.e., non-forest or 0% cover) in individual sources while considering their likely compatibility. Because *CCLIVE* was available for nearly all FIA plots after 2009, it was used to fill 0% cover in the *STEM* and *LINE* reference sources, which only have measurements for field visited plots. Limiting this filling to 0% cover enabled models for these variables to be more applicable across non-forest plots and the full range of cover from 0-100%, without the influence of the *CCLIVE* methods on the actual cover measures for model training. However, in the combinations below we used *CCLIVE* as the last step in filling *any* missing data for FIA plots in the training sample.

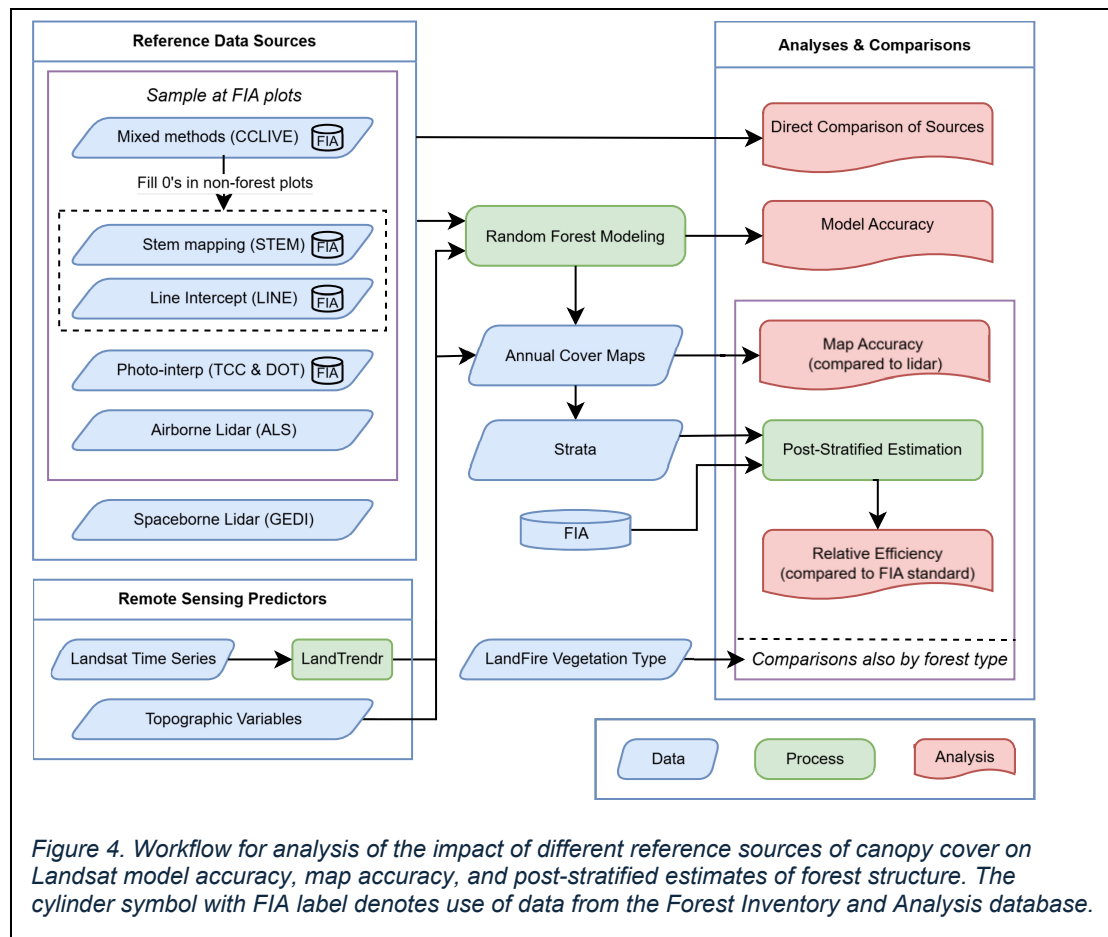
The first combination called *DOT > STEM > CCLIVE* indicates that *DOT* was selected first where available then *STEM* where available and then *CCLIVE* to fill remaining null values for the FIA sample. This combination was selected because *DOT* is an aerial-based measurement and therefore more likely to be related to Landsat than ground-based measurements, but it is not universally available. *DOT* was collected on all plots (forest and non-forest) as part of a special study for one panel and then a smaller subset of plots in other time periods. While stem-mapping estimates of cover can be created in a

consistent manner for any plot with live trees, it relies on crown allometry rather than direct cover measurement. For the remaining plots where neither *DOT* or *STEM* are available, cover was taken from *CCLIVE*, which in Colorado mostly used in situ ocular estimation with the aid of aerial imagery for forested plots. In this combination and the following, only a single measurement of a plot location was used for modeling to avoid bias in validation from temporal autocorrelation. The measurement for a plot location was selected in order of preference for the reference sources and then by most recent inventory year.

The second combination, *STEM* > *CCLIVE*, simplifies the above combination by relying on the consistent, albeit allometric-based, stem-mapping to provide estimates of cover for field-visited plots and using *CCLIVE* to fill in data gaps for plots not visited in the field. This represents a scenario in which future iterations of the NLCD TCC product could rely on cover estimates derived from manual measurements already collected as part of FIA ongoing operations (e.g., measured tree diameters or ocular estimates), rather than obtaining costly dot-grid measurements with aerial imagery.

The third combination, *LINE* > *DOT* > *CCLIVE*, favors ground or aerial measurements where available, without using allometry. This combination is based on the assumption that these measurements are more accurate than allometric-based or ocular estimates. *CCLIVE* is only used to fill in remaining data gaps, which are mostly 0's.

The fourth combination (*ALSc* > *STEM* > *CCLIVE*) and fifth combination (*ALSc4x* > *STEM* > *CCLIVE*) favor the use of ALS where available. ALS covers the entire state, but much of it is collected during leaf-off because of its primary application for topographic mapping. ALS has a much higher sampling density than the other direct cover measurements of *LINE* and *TCC* or *DOT*, and, unlike *LINE* that is based only 4 transects within each subplot, *ALSc* an aerial measurement with complete point sampling of the subplots. These factors could lead to *ALSc* having a closer relationship to Landsat spectral indices. We used *STEM*, which is available on all FIA sampled forest plots, as the secondary data source because the dot-grid measurements are less widely available, with *TCC* being collected as part of a short-term special study on ~20% of Colorado plots and other dot-grid measurements in *DOT* subsequently collected mostly on low canopy cover plots.



3.3 Landsat-based prediction of canopy cover

We modeled canopy cover from the above reference sources with predictor variables from moderate resolution remote sensing data to generate plot-level predictions and maps of canopy cover. We evaluated models by comparing pixel/plot-level accuracies and by comparing their use in post-stratified estimation of aboveground biomass and forest area. To create temporally dynamic predictors of forest conditions that could be matched to the time of reference data collection, we assembled annual Landsat composites of optical surface reflectance. Landsat Collection-2 Tier I Level 2 Surface Reflectance images for Landsat 8 (U.S. Geological Survey, 2020c), Landsat 7 (U.S. Geological Survey, 2020b), and Landsat 4-5 (U.S. Geological Survey, 2020a) were compiled for the growing season of each year (June 1st to September 30th) from 1984 to 2021 and filtered for clouds, cloud shadows, snow, and water using the provided Pixel Quality Assurance band and the Temporal Dark Outlier Mask (TDOM) algorithm (Housman et al., 2018). We created temporal composites by calculating the annual medoid

across all bands (Flood, 2013). A set of spectral indices were calculated for each temporal composite including the Normalized Difference Vegetation Index (Rouse et al., 1974), Normalized Burn Ratio (Key and Benson, 2006), the Tasseled-Cap Brightness, Greenness, Wetness (Crist, 1985; Huang et al., 2002), and Tasseled-Cap Angle (Powell et al., 2010). To reduce the influence of year-to-year changes in reflectance not due to real changes in tree canopy cover, we applied a temporal segmentation algorithm to the Landsat time series, which accounts for the effect of disturbances. The LandTrendr algorithm (Kennedy et al., 2018, 2010) was used to temporally segment each band and spectral index of the annual composite time series for each pixel in Google Earth Engine, and the fitted values were taken from the segmentation for modeling and mapping canopy cover.

Temporally static topographic predictors were included in the models with the above Landsat variables. A series of topographic variables was calculated from the U.S. Geological Survey's 10 m National Elevation Dataset resampled to 30 m using bicubic interpolation. These included the elevation in meters, the percent slope, the cosine of aspect, sine of aspect, and the cosine and sine of aspect multiplied by the percent slope (Stage, 1976). More complex topographic variables included the solar-radiation aspect index (Roberts and Cooper, 1989), the topographic position index calculated at scales of 90 and 990 m (Weiss, 2001), the continuous heat load index (Theobald et al., 2015), and the topographic diversity index (Theobald et al., 2015).

The above Landsat and topographic variables were used to predict canopy cover with random forest regression models (Breiman, 2001). Random forest is an ensemble decision tree model commonly used in remote sensing that can capture non-linear relationships, is robust to overfitting and collinearity, has internally generated accuracy, and often yields high accuracy (Belgiu and Drăguț, 2016). Our random forest models used 200 trees grown to full depth, and the square root of the total number of variables was randomly selected for consideration in splitting at each node. Model performance was evaluated with out-of-bag predictions using the root-mean-square-error (RMSE), the coefficient of determination (R^2), and the mean of residuals which we refer to as "bias". Out-of-bag error is an unbiased indicator of generalization error that has a lower computational cost than cross-validation (Breiman, 1996). Because of differences in the availability of the cover reference sources, the models each have different distributions for training and validation, which complicates the comparison of model performances. To

enable a comparison based on the same sample, annual maps of canopy cover were then generated from the models of each reference source for all of Colorado. These maps were evaluated by comparison to the lidar cover maps where and when available, considering airborne lidar as a reliable, high sample density basis for accurate measurement of cover.

3.4 Post-stratified estimation of aboveground biomass

Maps of canopy cover developed from each reference source were used with FIA plots for post-stratified estimation of live aboveground biomass in Mg ha^{-1} (AGB) and forest area in Mha. The canopy cover maps were split into 3 strata of non-forest (0-9%), low (10-29%), and high (30%-100%) (Freeman et al., 2024). Each plot was assigned to the stratum it intersected, and a stratum's weight was determined by its proportion of the total map area. We used the R package FIESTA version 3.6.4 (Frescino et al., 2023) to calculate the post-stratified mean and variance of AGB and forest area for all counties in Colorado (i.e., county-level) and for the state as a whole for the 2019 evaluation year (i.e., EVALID=081901). The mean and variance of AGB and forest area were also obtained with the Horvitz-Thompson estimator by treating the FIA sample as a simple random sample (SRS), without post-stratification. To evaluate the gain or loss in precision of using maps derived from each reference source for post-stratified estimation, we calculated the relative efficiency (i.e., $RE = \frac{V_{base}}{V_{test}}$) with the SRS serving as the base method for comparison. RE values greater than one indicate a gain in precision and values less than one indicate a loss in precision relative to the base method.

3.5 Comparison of reference sources

Compiling the above data allowed us to compare reference sources in four ways: directly, by out-of-bag model performance metrics, by map accuracy relative to lidar cover maps, and by the relative efficiency (RE) of post-stratified estimators of AGB and forest area (Figure 4). Canopy cover measurements from the reference sources were directly compared where they were obtained at the same spatial location. *STEM*, *TCC*, *DOT*, *CCLIVE*, *LINE* and *ALSc* were all from FIA plots, though the dates of collection (i.e., imaging year) for *DOT*, *TCC*, and *ALSc* could be different from the measurement year of *STEM*, *CCLIVE*, and *LINE*. *ALSc* was also generated at GEDI footprints for comparison with *GEDIc*. For direct comparison, the two reference sources being compared were limited to measurements that were within 4 years of each other. At the FIA plot-level, we also calculated the correlation between each cover

source or combination with the forest attributes of interest (i.e., forest presence and AGB) since the strength of this relationship should also be a factor in determining the map layers' ability to reduce estimator variance through plot stratification (Westfall et al., 2021). Plot-level forest land use was based on an FIA determination of whether a plot is likely to have a forest condition based on previous measurements and interpretation of aerial imagery; this forest presence variable was used as a proxy for forest area because it is plot-level variable that is available for all FIA plots. We also compared the performance of remote sensing models derived from the different reference sources by their out-of-bag model R^2 , RMSE, and bias. The accuracy of maps, derived from the different sources, was investigated by comparison to the 30 m airborne lidar maps of canopy cover as described in section 3.2.5. We also then compared the variance and RE of post-stratified estimators and SRS estimators of AGB and forest area that were derived from stratification layers based on the maps from different cover reference sources. These comparisons were made at the level of the entire state and FIA estimation units (i.e., counties).

We also wished to know if the results of the map accuracy and forest variable comparisons differed by forest type. To perform this forest type level analysis for the map accuracy comparison, we grouped the pixels of each map into forest types as determined by the 2016 LANDFIRE Existing Vegetation Type (EVT) map (LANDFIRE, 2016). The LANDFIRE EVT map was simplified by manually reclassifying the group names as defined in Table S 2 in the appendix. For simplicity, our analysis of map accuracy by forest type focused on the four dominant forest types in Colorado, according to LANDFIRE EVT, which comprised 80.5% of the forest class area. These forests and their percentage of Colorado forest area were aspen (15.5%), pinyon-juniper (26.0%), ponderosa pine (14.6%), and spruce-fir (24.4%), which roughly match to proportions estimated with the FIA ground sample

(<https://research.fs.usda.gov/products/dataandtools/forest-inventory-and-analysis-one-click-state-factsheets>). For analyzing post-stratified estimates by forest type, FIA plots were effectively grouped based on the majority forest type code of the plot (i.e., FORTYPECD group in the FIA database). The forest type group codes that were analyzed align with the forest types used in the lidar map analysis (section 3.3) and include: pinyon/juniper (called pinyon-juniper), fir/spruce/mountain hemlock (called spruce-fir), aspen/birch (called aspen), and ponderosa pine. Mean estimates of AGB and forest area,

their variance, and their *REs* were calculated for the state and county areas by forest type using the canopy cover maps derived from each reference source for plot stratification.

The above comparisons allowed us to determine the relative benefit of using different reference sources of canopy cover independently and in select combinations, not just for map accuracy directly but also for the impacts of using the maps to generate post-stratified population estimates of forest structure and area.

4 Results

4.1 Direct comparison

All cover measurement sources on FIA plots had linear relationships when directly compared to each other (Figure 5) though the strength of that relationship varied by the pair (Table 2). Aside from comparisons using the *LINE* and *STEM* sources, all comparisons had regressions that fell close to the 1:1 line (Figure 5), with slopes of 0.85 to 0.94 and intercepts of 2.01 to 5.06 (Table 2). Comparisons with *LINE* and *STEM* often had much higher intercepts and lower slopes because they are only available on field visited plots which are mostly forested, and thus they are not zero-inflated like the other reference sources. Filling plots with 0% cover in *LINE* and *STEM* with data from *CCLIVE* brought regressions closer to the 1:1 line and increased the strength of the relationships with these sources dramatically, with increases in R^2 of 0.28 to 0.4 in comparisons using *STEM* and 0.07 to 0.64 in comparisons using *LINE* (Table 2). Even before filling 0% cover, *LINE* and *CCLIVE* had the strongest direct relationship, likely because field crews that collect the *LINE* measurement use it to inform their recording for *CCLIVE*. *DOT* and *CCLIVE* likewise had a strong relationship because dot-grid measurements comprise 31% of the *CCLIVE* mixed methods variable. Of the comparisons using single-method measurements (i.e., not *CCLIVE*), *LINE* and *STEM* had the strongest relationship before filling 0's ($R^2=0.62$), though the intercept was relatively high at 7.93. After filling 0's, *LINE* and *STEM* had the strongest overall relationship ($R^2=0.9$, $RMSE=7.1$) of the single methods, and a regression that was close to 1:1 (intercept=0.76, slope=1.03).

Aerial measurements of cover had some surprising differences. *ALS* and *DOT* had one of the strongest relationships of single method sources and the bias was low at -1.19, but the R^2 was still only 0.59 and the $RMSE$ was 9.96. The lack of a stronger relationship may be due a mismatch in spatial coverage between *ALSc* and *DOT* on FIA plots; *ALSc* is calculated over individual subplots, whereas

DOT uses a dot-grid distributed within a 43.9 m radius circle that encompasses all the subplots and the intervening space. The comparison between all source pairs, including *ALSc* and *DOT*, could also be hampered by intervening disturbances since we only used a temporal limitation (i.e., 4 years) rather than identifying and filtering plots with intervening fires and harvests. Comparison of GEDI and ALS cover over GEDI footprints had a curvilinear relationship with GEDI cover frequently being less than 30% even as ALS cover approached 90%. In spite of this, the regression of *ALSc* on *GEDlc* still had a slope of less than 1 because there were also many instances where GEDI cover was 100% when ALS cover was much lower, which can be seen as a faint vertical line on the right side of *GEDlc* and *ALSc* plot in Figure 5.

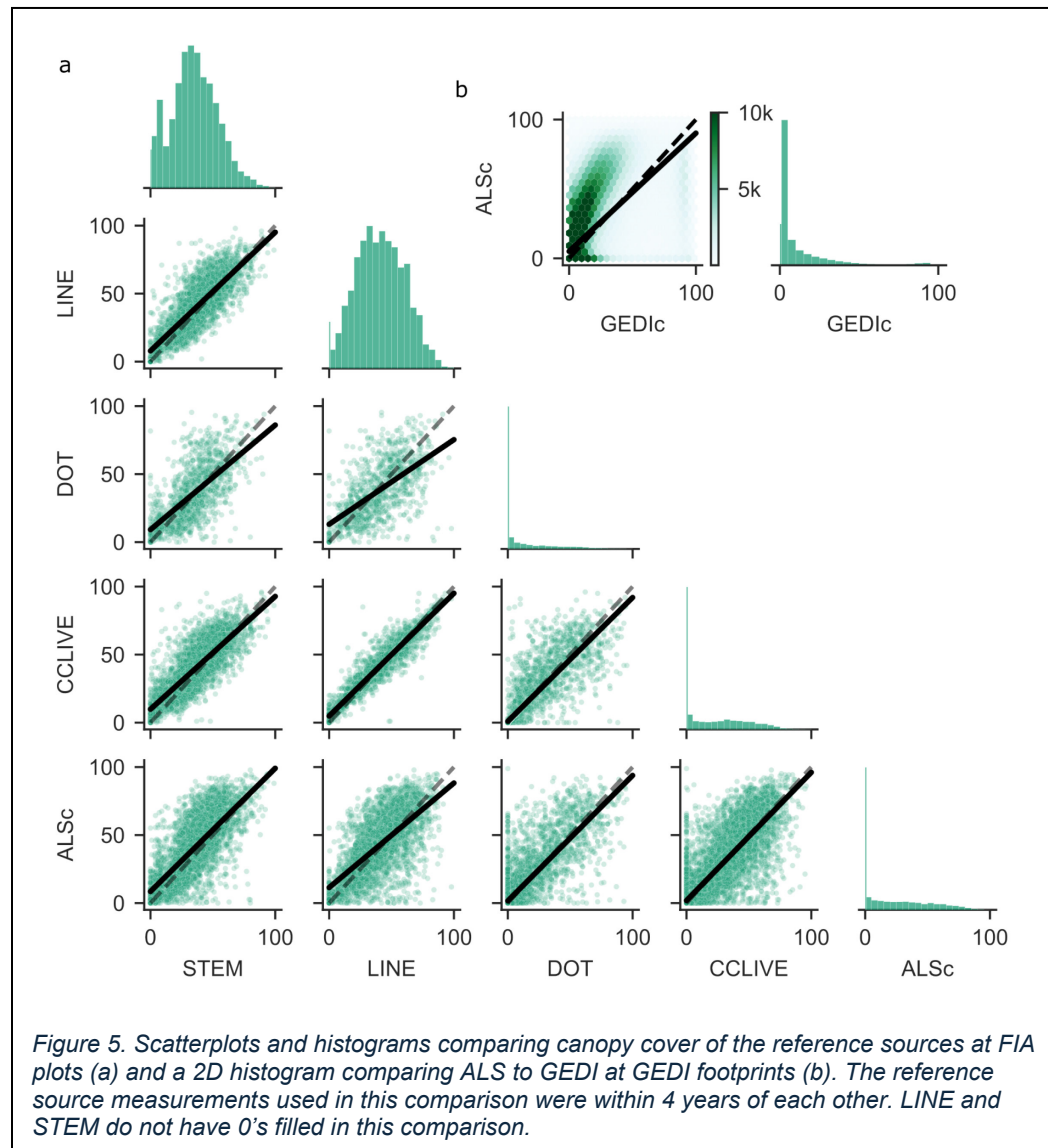
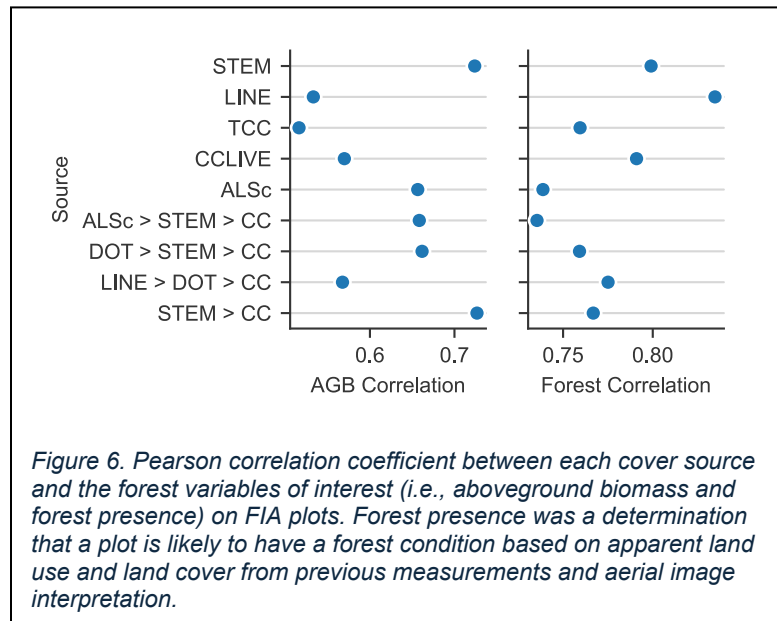


Table 2. Relationship between cover sources without filling 0's using CCLIVE (left) and with filling 0's in LINE and STEM using CCLIVE (right) and in bold.

Y	X	Without Filling 0's						With Filling 0's (bold)					
		N	R ²	Bias	RMSE	Intercept	Slope	N	R ²	Bias	RMSE	Intercept	Slope
ALS	GEDI	3052005	0.37	-3.53	18.62	5.06	0.85	-	-	-	-	-	-
ALS	LINE	2002	0.39	-1.93	17.65	11.1	0.77	5642	0.77	-1.36	11.55	2.02	0.95
ALS	CCLIVE	6827	0.74	-1.18	12.04	2.04	0.94	6827	0.74	-1.18	12.04	2.04	0.94
ALS	DOT	2551	0.59	-1.19	9.96	2.01	0.85	2551	0.59	-1.19	9.96	2.01	0.85
ALS	STEM	2488	0.5	-5.3	16.02	8.28	0.91	6128	0.78	-2.77	11.19	2.05	1.05
LINE	CCLIVE	3198	0.9	0.94	6.13	-1.12	1	9203	0.97	0.33	3.61	-0.09	0.98
LINE	DOT	965	0.15	-1.95	18.84	18.16	0.57	6371	0.79	-0.22	7.53	0.73	0.91
LINE	STEM	3180	0.62	-3.22	12.06	7.93	0.87	9185	0.9	-1.12	7.1	0.76	1.03
CCLIVE	DOT	7367	0.77	-0.37	7.84	0.96	0.91	7367	0.77	-0.37	7.84	0.96	0.91
CCLIVE	STEM	3899	0.6	-4.02	12.09	9.81	0.83	9903	0.88	-1.58	7.59	1.3	1.02
DOT	STEM	1214	0.41	-1.36	16.49	9.16	0.77	6620	0.81	-0.32	7.26	0.55	0.96

The correlation between each cover source and AGB on FIA plots was between 0.52 and 0.73, while the correlation with forest land use ranged from 0.74 to 0.83 (Figure 6). STEM and LINE had the highest correlation with forest land use, possibly because they are only measured on field-visited plots that are likely to have a forest land use. *STEM* and the closely related combination, *STEM* > *CC*, had the highest correlations with AGB. *STEM* and AGB are both directly based on tree diameters.

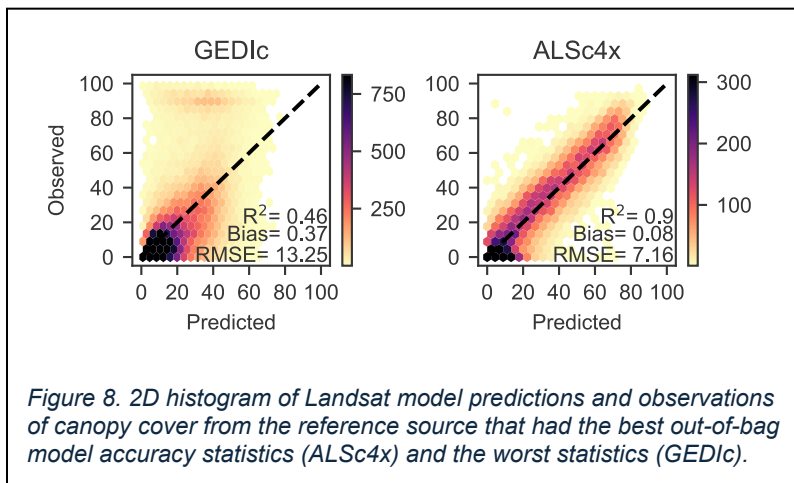
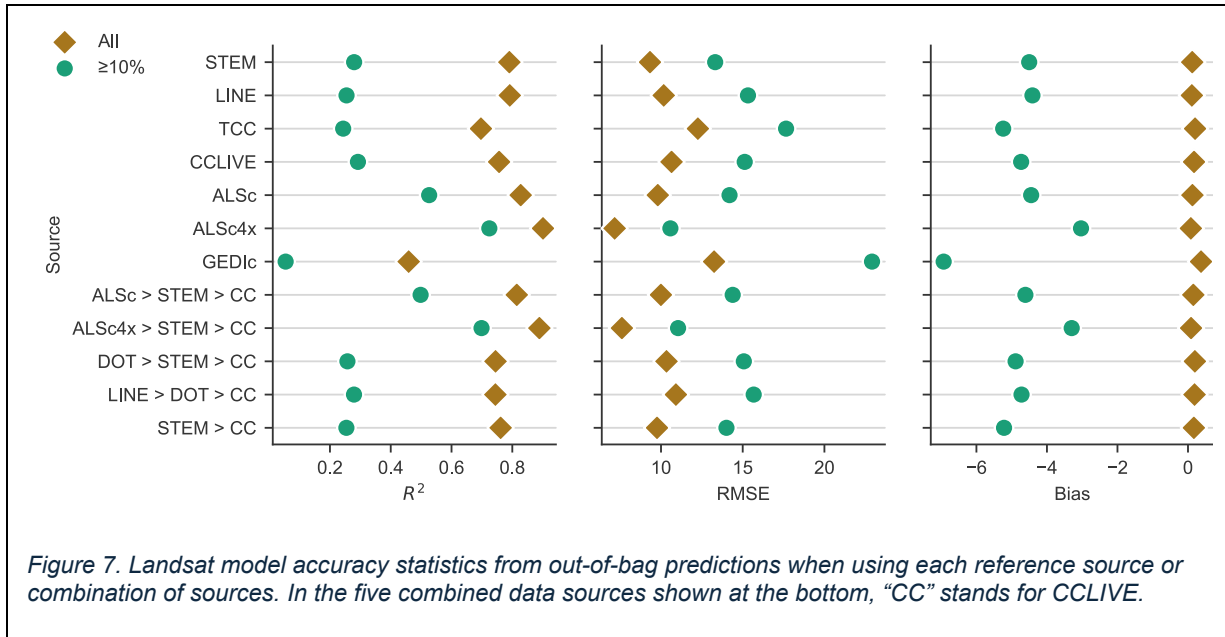


4.2 Landsat-based model performance

Landsat-based models using reference data on FIA plots had fairly similar and high performance when considering the full range of canopy cover, with R^2 from 0.70 to 0.90, RMSE from 7.16 to 12.26, and biases of effectively 0 (Figure 7). The primary exception was *GEDIc*, which had much lower performance for both all cover ($R^2=0.46$, RMSE=13.25) and cover of at least 10% ($R^2=0.05$, RMSE=22.91). For all

datasets, performance was lower when considering only sample units with cover $\geq 10\%$. On average across all datasets, R^2 declined by 0.40, RMSE increased by 4.84, and bias went from being near zero to a mean of -4.67 when constraining the analysis to samples with cover $\geq 10\%$. The negative bias in areas with cover $\geq 10\%$ indicates a model tendency to underestimate higher levels of cover regardless of the reference dataset used. The regression towards the mean that leads to this underestimation of high values can be seen in plots of observed and predicted cover for both the best performing model, using *ALSc4x*, and the worst performing model, using *GED/c* (Figure 8). All models also overestimated low values of canopy cover (i.e., cover $< 10\%$) with biases of 1.68 to 3.36. Regression towards the mean is a known consequence of averaging decision trees with random forest models (Zhang and Lu, 2012).

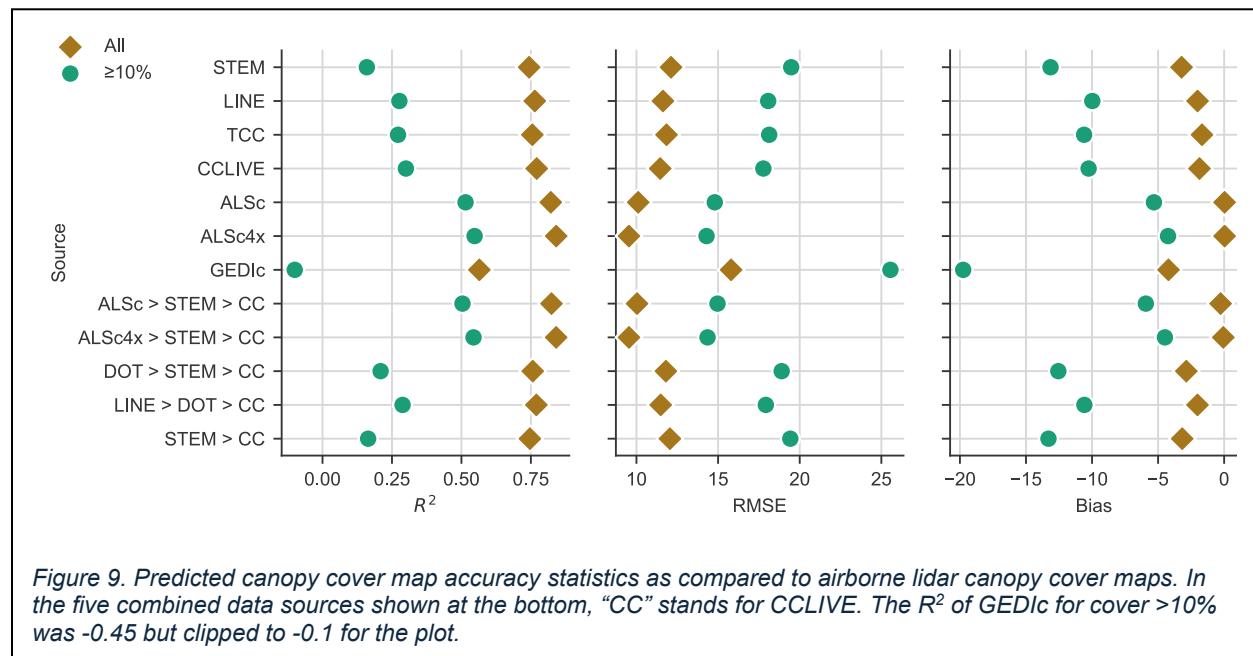
The canopy cover datasets derived from ALS had the strongest correspondence with the Landsat metrics and other spatial predictors, which is not surprising given that ALS and Landsat are both aerial measurements that are mostly close to nadir and that ALS has a high sample density on each plot (i.e., at least 200 points). Increasing the sample size of ALS from 10,167 for *ALSc* to 37,778 for *ALSc4x* improved overall performance, but especially improved performance in areas with cover $\geq 10\%$, with an increase in R^2 of 0.20, decrease in RMSE of 3.62 and reduction in absolute bias of 1.41. Models that were based on some form of non-automated measurements (i.e., using *STEM*, *LINE*, *TCC*, or *CCLIVE*) all resulted in similar performing Landsat models. Combining these cover reference sources often led to model performance that was similar to the best single data source. For example, *DOT > STEM > CC* (RMSE=10.34, n=11159) and *STEM > CC* (RMSE=9.76, n=11059) had slightly lower performance than *STEM* alone (RMSE=9.33, n=9990), despite the higher sample size. Combining these other datasets with the *ALSc* measurements also slightly degraded model performance over using *ALSc* or *ALSc4x* alone.



4.3 Map accuracy

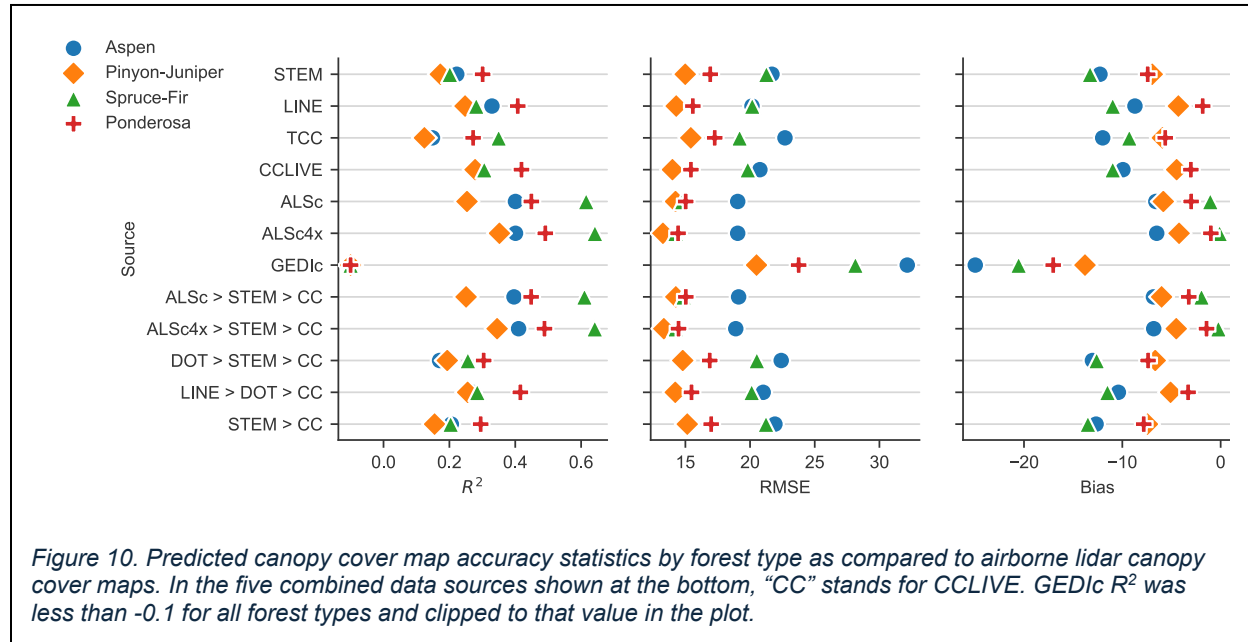
Performance of the Landsat-based predicted canopy cover maps in comparison to airborne lidar cover maps, also called ALS observed, was in general similar to the out-of-bag Landsat model accuracies reported in section 4.2, but absolute bias was no longer negligible. Most overall map R^2 values were between 0.74 and 0.84; RMSEs were 9.54 to 12.12; biases were -3.22 to 0.04. The exception again was *GEDlc*, which had by far the lowest performance when considering all data ($R^2=0.56$, RMSE=15.80, bias=-4.21), and *GEDlc* performance also dropped substantially when considering only areas with cover $\geq 10\%$ in the lidar maps ($R^2=-0.45$, RMSE=25.55, bias=-19.75). Performance also declined in areas with cover $\geq 10\%$ for the other datasets but was less considerable, with an average decline in R^2 of 0.44,

increase in RMSE of 6.04, and increase in absolute bias of 7.56. Not surprisingly, the predicted cover maps based on *ALSc* had the highest performance when compared to the observed ALS cover maps, but results for the high intensity sampling *ALSc4x* were only slightly better. Also, combination sources that mixed FIA field sources with *ALSc* had negligible differences in map performance from *ALSc* only, even though the accuracy evaluation was to the ALS cover maps. Predicted cover maps derived from a combination of sources often had nearly the same performance statistics as the maps derived from the first dataset in the combination.

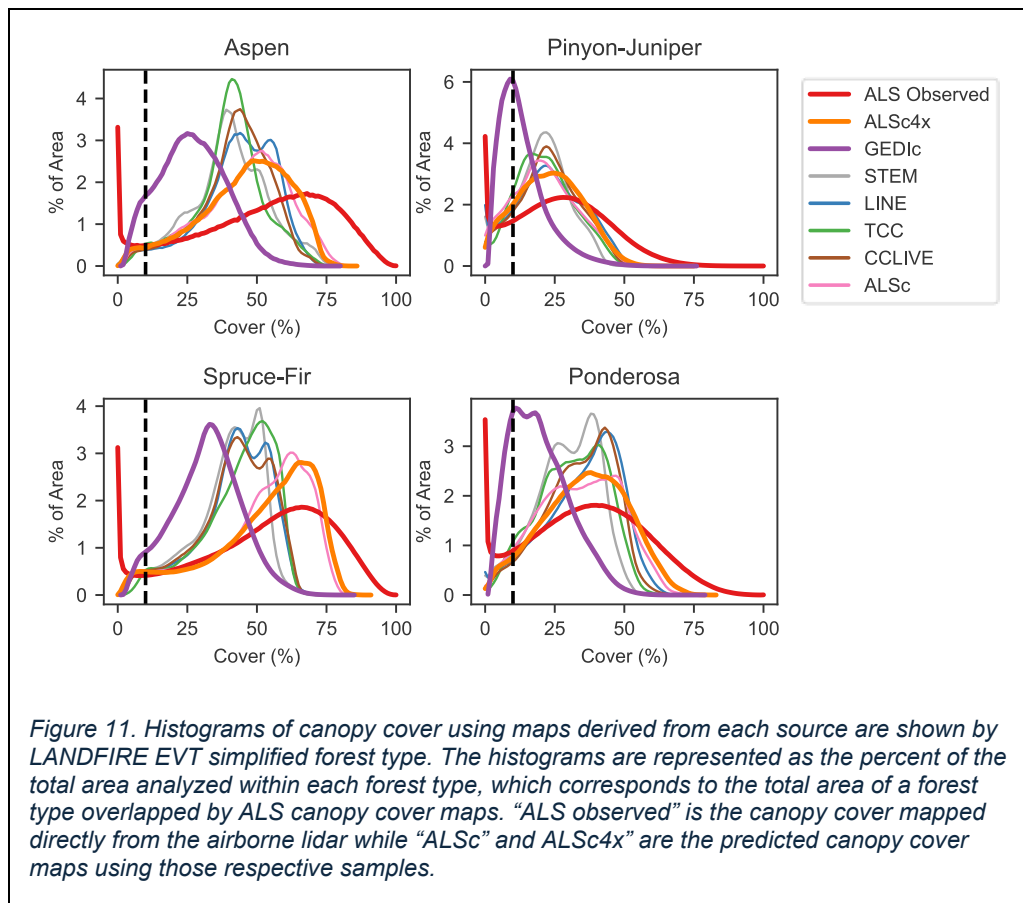


When parsing map accuracy by simplified LANDFIRE EVT forest type there are some consistent trends across datasets (Figure 10). In the maps created with the non-automated measurement cover sources (i.e., *STEM*, *LINE*, *TCC*, and *CCLIVE*) as the first or sole source in model development, ponderosa pine forests had the highest R², whereas spruce-fir forests had by far the highest R² for the *ALSc*-based datasets. Maps from *ALSc*-based cover sources substantially outperformed the other sources in spruce-fir forests, with an improvement of 0.37 in R², 6.1 in RMSE, and 11.6 in bias between *ALSc4x* and other non-lidar sources, for example. For RMSE the ranking of performance by forest type was more consistent across all datasets. Pinyon-juniper was always the lowest RMSE, typically followed by ponderosa pine, then spruce-fir, and then aspen with highest RMSE. Cover in aspen forests was also the most strongly underestimated (i.e., greatest negative bias) across most of the datasets. The *ALSc*-

based datasets had nearly 0 bias overall (Figure 9), but when parsed by forest type (Figure 10), spruce-fir was the only type with a nearly 0 bias. The *ALSc4x* predicted cover maps had the lowest absolute bias, first or second lowest RMSE, and first or second highest R^2 for all forest types. This result is expected given that it is the same metric used in the airborne lidar cover maps and it has the highest training sample size. *CCLIVE* was often the highest ranking non-ALS single source dataset even though it did not have the closest correspondence to *ALSc* in the direct comparison (Figure 5; Table 2).



The higher performance of the *ALSc4x* maps relative to the cover source maps, is also reflected in histograms of canopy cover by LANDFIRE EVT forest type, where it most closely matches the distribution of the observed ALS maps (Figure 11). All the predicted maps far underestimate the area with 0% cover in every forest type when compared to the ALS cover maps directly calculated from ALS point clouds (i.e., “ALS Observed”), and they underestimate the area with very high cover. This reflects the compression towards the mean in the random forest Landsat models, such as can be seen in Figure 8. The combination datasets had similar distributions (not shown) to those of their first selected single source. Underestimation of the area of high and even moderate cover values is most strongly pronounced in the *GED1c* histogram, which also has a much larger area of non-forest in the pinyon-juniper and ponderosa pine classes if using a 10% threshold.

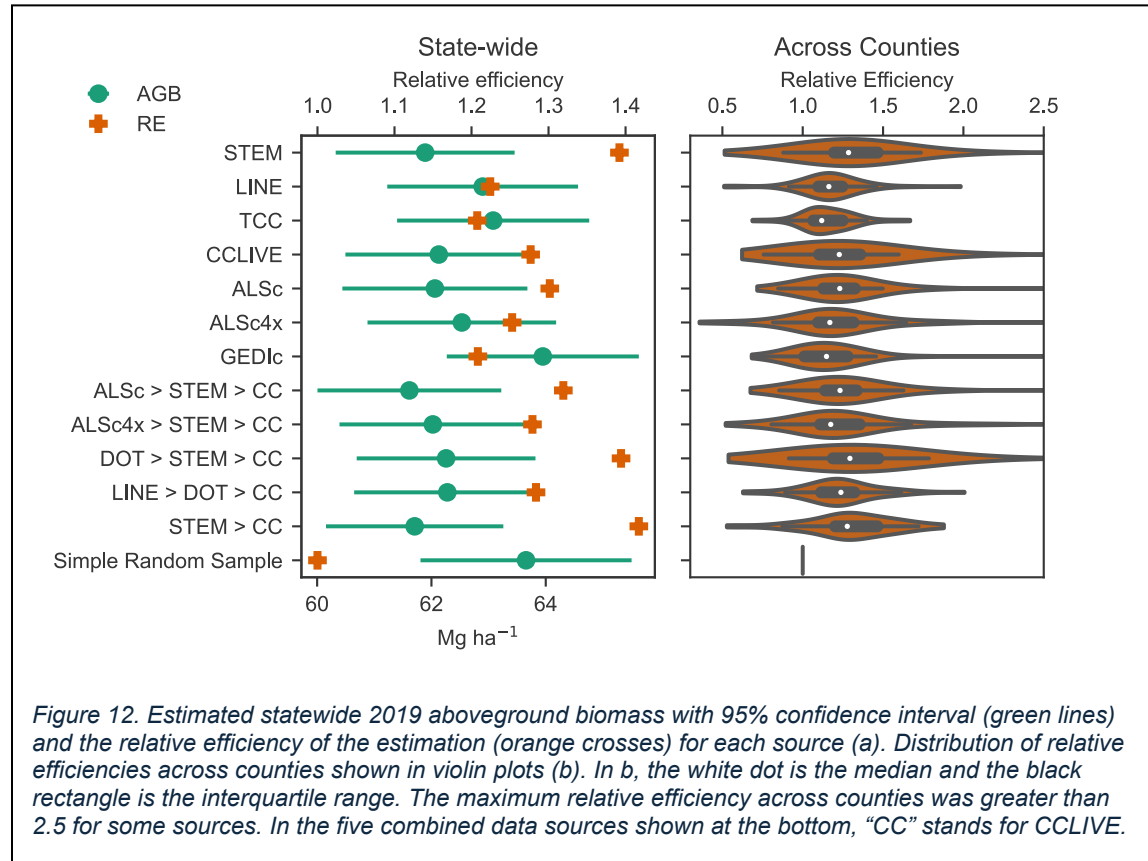


4.4 Post-stratified estimation of aboveground biomass

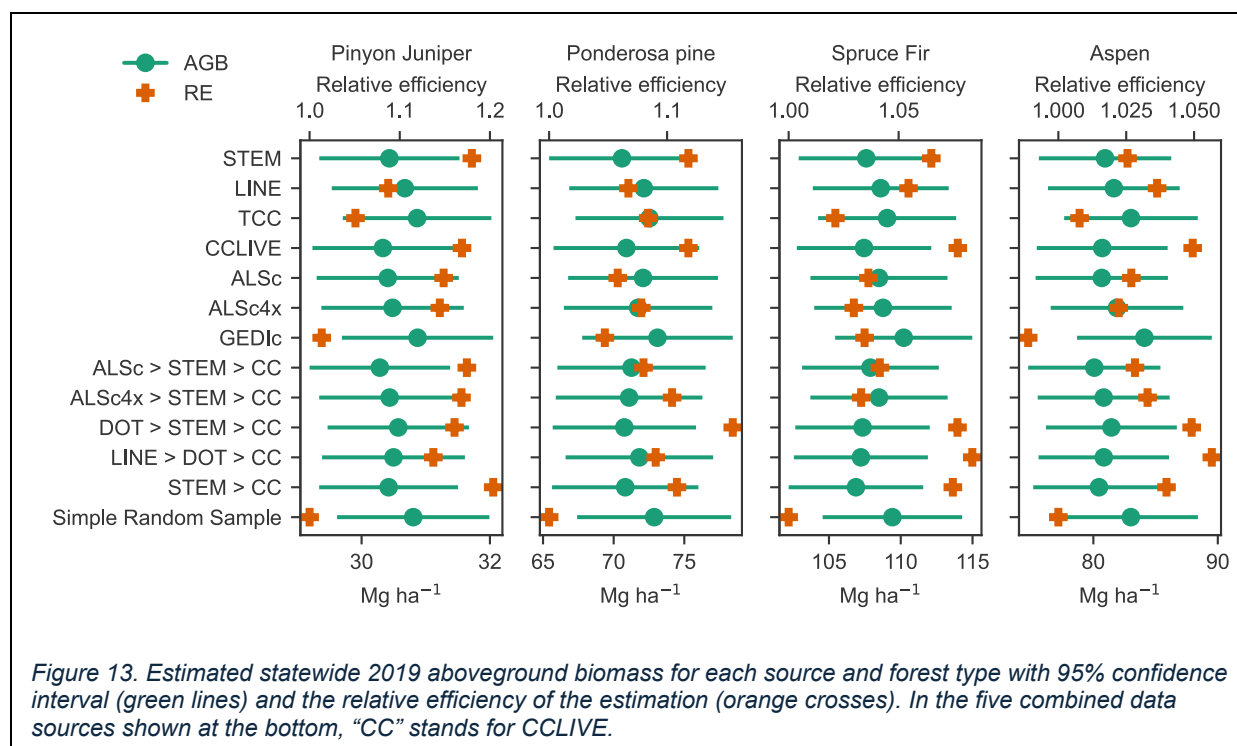
Estimates for statewide mean AGB were between 61.6 and 63.9 Mg ha⁻¹ when using post-stratification with the different cover source maps or a simple random sample (Figure 12). The 95% confidence intervals overlapped for all estimates and were 3.1 to 3.7 Mg ha⁻¹ in size, which was 5.0% to 5.8% of the estimate. *STEM* had the highest relative efficiency (*RE*) of any single source at 1.39 and *STEM* > *CC* had the highest overall *RE* at 1.42. *GEDlc* and *TCC* both had the lowest *RE* at 1.21. *ALSc4x* had a lower *RE* (1.25) than *ALSc* (1.30) despite the use of a larger sample. Using a combination of cover sources increased *RE* by 0.02 to 0.19 in comparison to the *RE* from the first single source used in the combination, but when compared to the best single source in the combination the change in *RE* ranged from -0.11 to 0.03.

When looking across counties for all sources, *RE* ranged from 0.36 to 7.0 (Figure 12). The range of county-level *RE*'s varied substantially between sources, such as *TCC* which had *RE*'s of 0.69 to 1.67 (i.e., range of 0.98) and *DOT* > *STEM* > *CC* which had *RE*'s of 0.54 to 7.0 (i.e., range of 6.46). However, the

interquartile range in *RE* overlapped for all sources and the medians differed by at most 0.18, with 1.12 for *TCC* being the lowest and 1.29 for *DOT* > *STEM* > *CC* being the highest. Using combinations of sources did not appear to have a substantial impact on the distribution of county-level *RE*'s either.



Estimates of mean AGB by forest type were similar across all cover sources with ranges of 30.3 to 30.9 for pinyon-juniper, 70.6 to 73.1 for ponderosa pine, 106.9 to 110.2 for spruce-fir, and 80.1 to 84.1 for aspen (Figure 13). The width of 95% confidence intervals (i.e., the precision of the estimate) also had little variation between sources within a forest type, with the ranges being only 0.21 for pinyon-juniper, 0.76 for ponderosa pine, 0.38 for spruce-fir, and 0.35 for aspen. The absolute widths of confidence intervals increased with higher mean biomass, but forest types with a larger area in Colorado tended to have smaller relative confidence interval widths. The average confidence interval width as a percentage of the mean biomass was 7.3% for pinyon-juniper, 14.6% for ponderosa pine, 8.8% for spruce-fir, and 13.0% for aspen. Variations in *RE* were less consistent across forest types and sources but only differed by at most 0.20, which could be considered negligible differences (Czaplewski and Patterson, 2003).

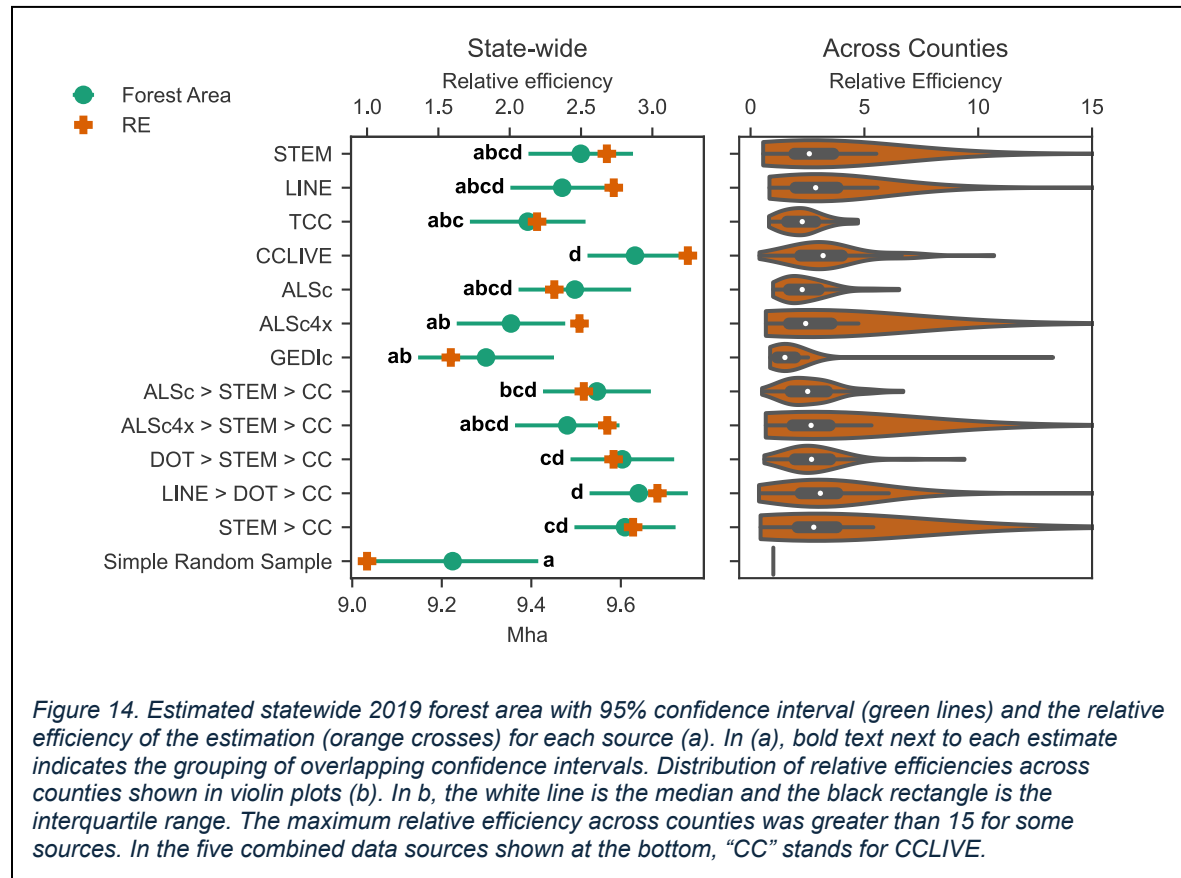


4.5 Post-stratified estimation of forest area

Estimates for statewide forest area were between 9.22 and 9.64 Mha when using post-stratification with the different cover source maps or a simple random sample (Figure 14). Since the mean AGB values all stem from design-unbiased estimators, they are all equally valid, and we would expect them to have only minor differences. However, the 95% confidence intervals did not overlap for all estimates. For example, the estimates from SRS were significantly lower than those from *CCLIVE*, *ALSc* > *STEM* > *CCLIVE*, *DOT* > *STEM* > *CCLIVE*, *LINE* > *DOT* > *CCLIVE*, and *STEM* > *CCLIVE*. The width of the confidence intervals were 0.21 to 0.38 Mha, which was 2.2% to 4.2% of the estimate. *CCLIVE* had the highest relative efficiency (*RE*) at 3.25 and *GEDlc* had the lowest *RE* at 1.59. Using a combination of cover sources increased *RE* by 0.18 to 0.54 in comparison to the *RE* from the first single source used in the combination, but *RE* decreased for all combinations by 0.21 to 0.73 when compared to the best single source in the combination.

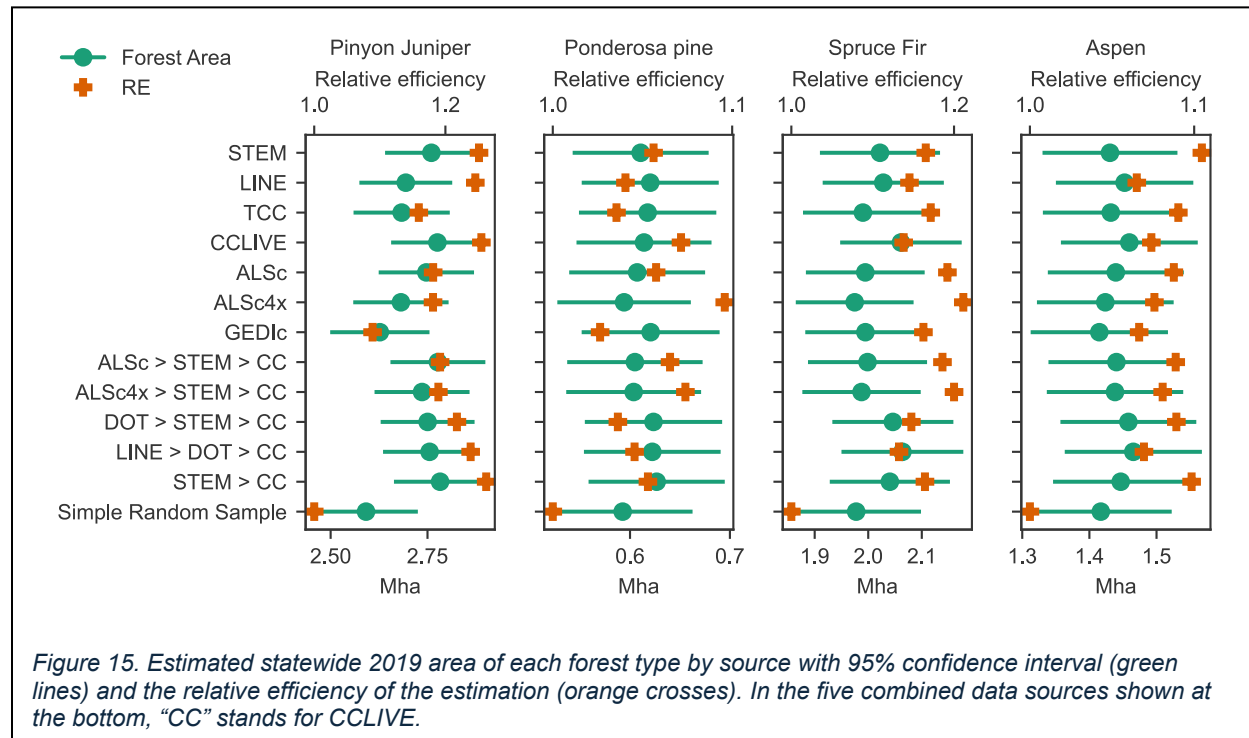
When looking across counties for all sources, the *RE* for forest area estimates ranged from 0.37 to 70.8 (Figure 14). *GEDlc* was the only source that had an interquartile range in *RE* that did not overlap with some of the other sources. The median *RE* for *GEDlc* was also the lowest at 1.51, *CCLIVE* had the

highest median *RE* at 3.19. The use of a larger sample with *ALSc4x* led to a minor improvement of 0.18 in *RE* at the state-wide level and an increase in median *RE* of 0.15 at the county level when compared to the single intensity *ALSc*. Combining sources did not substantially improve nor worsen the distribution of *RE* in comparison to using single sources.



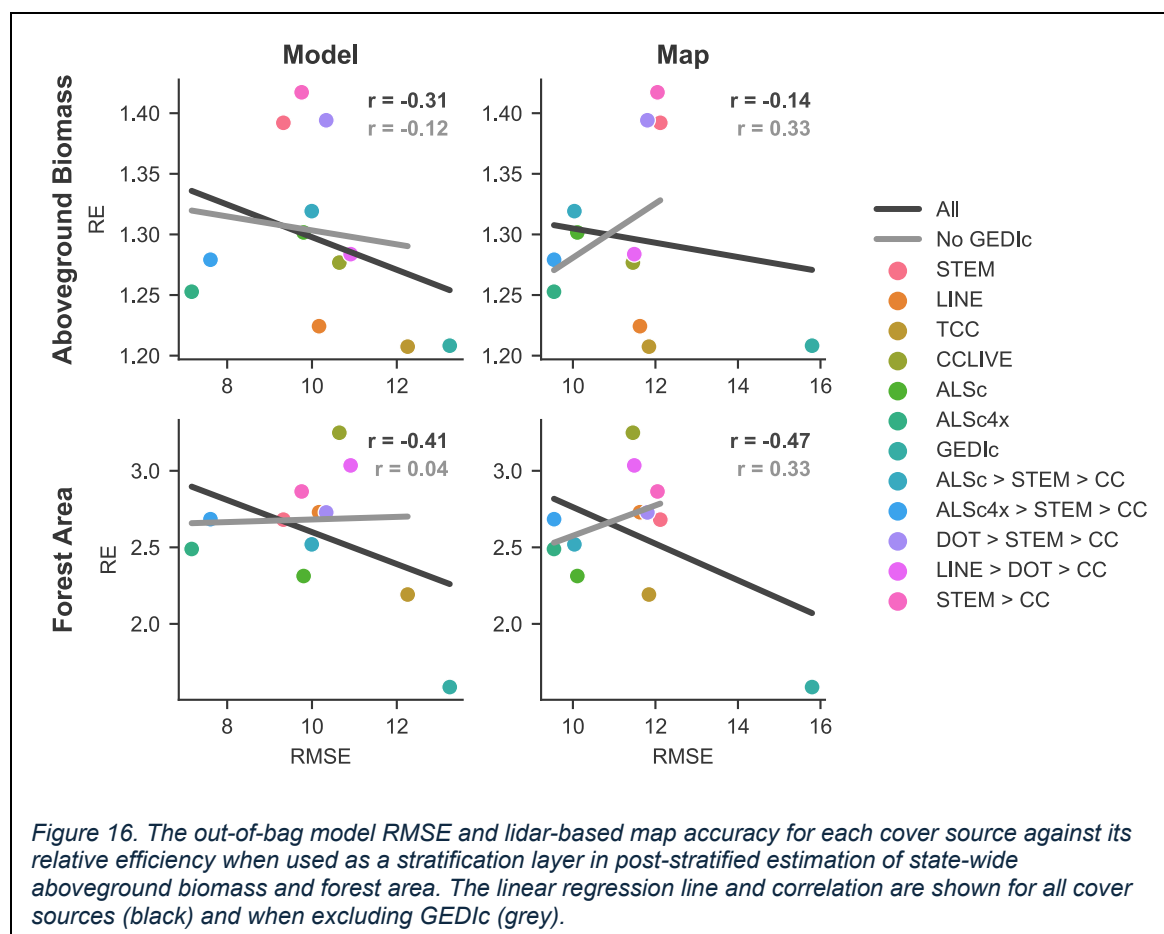
Estimates of forest area were more similar across cover sources when looking at individual forest types, and the 95% confidence intervals overlapped for all sources in all forest types (Figure 15). The *RE* for specific forest types also had much less variation between sources than when considering all forest statewide, with stratified estimation providing much smaller reductions in variance than at the statewide level. The highest *RE* was 1.26 for pinyon-juniper with *STEM* > *CC*, 1.1 for ponderosa pine with *ALSc4x*, 1.21 for spruce-fir with *ALSc4x*, and 1.1 for aspen with *STEM*. The relative width of confidence intervals (i.e., as a percentage of the estimate) increased with decreasing forest area, being on average 9.0% for pinyon-juniper, 11.2% for spruce-fir, 14.1% for aspen, and 22.3% for ponderosa pine. The *RE* ranking of sources was even less consistent across forest types than in the AGB analysis (Figure 13). *STEM* had

the highest mean rank of 4.0, and *STEM* and *STEM > CCLIVE* had nearly the same average *RE* across forest types of 1.444. *GEDlc* again had the lowest mean rank (10.75) and lowest mean *RE* (1.09) across forest types.

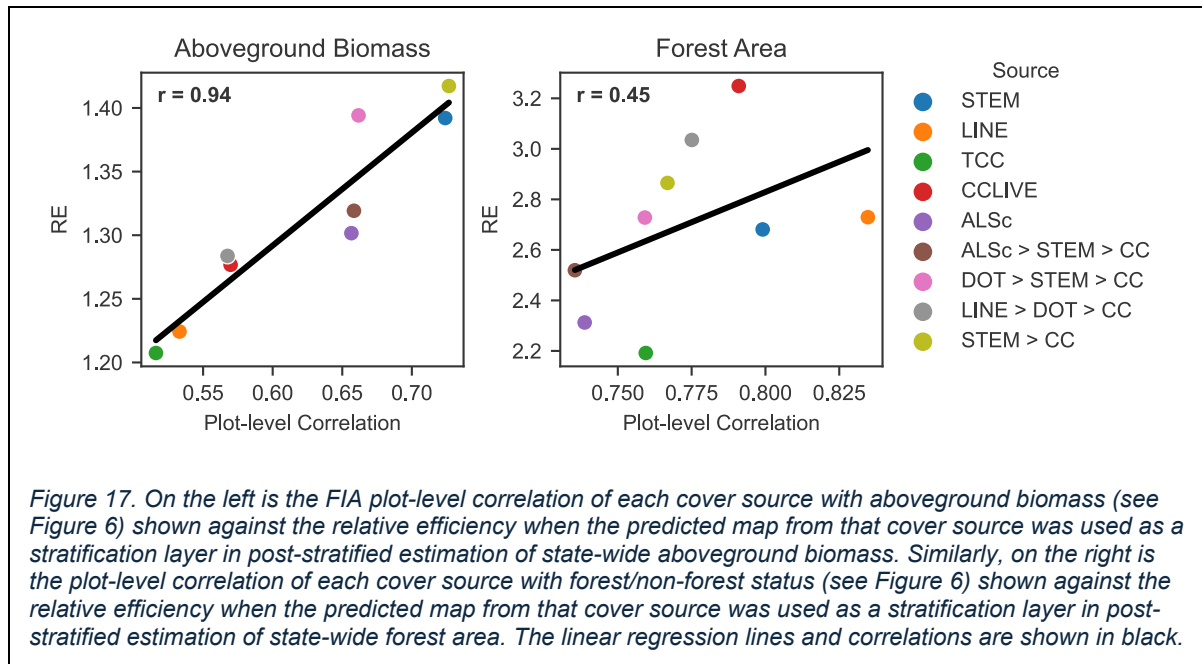


4.6 Canopy cover source relationship with estimator variance

The relative efficiency of post-stratified estimators using each cover reference source had a weak negative correlation with out-of-bag model RMSE and lidar map RMSE (Figure 16). However, the relationship was largely driven by *GEDlc*, and correlations became weaker or flipped from negative to positive when excluding it. Many of the points fell in a narrow range of RMSE of around 10% for model accuracy and around 12% for map accuracy, and yet within this narrow range of accuracies, *RE* values had a fairly wide range for forest area and modest range for AGB.



The relative efficiency of the AGB and forest area post-stratified estimators was much more strongly related to the plot-level correlation of each cover source with the associated attributes (Figure 17). With a Pearson correlation coefficient of 0.94, the association of a particular cover measurement with AGB at the plot-level can explain almost all the variation in RE of the estimator at the state-level. The relationship was weaker with plot-level forest presence and state-level forest area ($r=0.45$), being leveraged largely by the lower relative efficiencies of *STEM* and *LINE*.



5 Discussion

This study primarily sought to understand how different cover reference sources and their resulting cover maps could be used to improve the precision of post-stratified estimators of forest structure. Improving estimator precision is critical for reducing the effective number of field plots and thus the cost of national forest inventory operations and for reducing forest reporting uncertainties for geographic and administrative units to aid in timber and carbon management, including for forest conservation incentives (e.g., REDD+). What we found was that the relative efficiency (RE) of post-stratified estimators depended far more on the strength of the plot-level relationship between a given cover reference source and the variable of interest (i.e., AGB or forest area) than the accuracy of the map layer generated with different cover sources as training data (Figure 17). This can be most clearly seen in the relationship between AGB and *STEM* which had highest plot-level correlation and the highest RE , even though *STEM*'s model and map performance metrics were not as high as those based on *ALSc4x*. This is likely because both *STEM* and AGB are based on tree diameter measurements. The relationship between plot-level correlation and estimator precision was slightly weaker when looking at forest area, which was perhaps because all cover sources were strongly related to forest presence without much variation (Figure 6).

The importance of the relationship between the variable of interest and the stratifying variable is a tenet well-grounded in survey sampling theory (Cochran, 1977). This principle has been supported in

subsequent empirical studies in post-stratified estimation of forest attributes using remote sensing derived strata (McRoberts et al., 2014, 2012; Westfall et al., 2019). In many cases using a classification of the variable of interest as the stratifying layer yields optimal results, a method termed endogeneous post-stratification by Breidt and Opsomer (2008).

The relationship of model or map accuracy with *RE* was stronger for forest area than for AGB, but in both cases there was little effect within the range of model or map accuracy for most cover sources. For both forest area and AGB, the correlations of *RE* with map accuracy were largely driven by a single data point with especially low accuracy - *GED1c*. This could indicate that the *RE* of estimators may indeed be sensitive to cover mapping accuracy when considering a larger range of potential accuracies. Post-stratification *RE* can be vastly improved when using an ideal stratification (Westfall et al., 2021), and this was effectively demonstrated by Westfall (2019) which found that plot-level photo-interpretation yielded higher *RE* than less accurate maps used for stratification. In principle, error in the stratifying layer should only lead to an increase in variance of the estimator when it affects sample assignment to incorrect strata, reducing the homogeneity within strata, and thus depends mainly on error near the strata boundaries (Cochran, 1977). Our study only used three strata — no forest (0-10), low forest cover (10-30), and high forest cover (30-100%), based on FIA Rocky Mountain Research Station's post-stratification routine currently used in Colorado (Freeman et al., 2024). Had we used a larger number of strata, such as 4-6 as is often recommended (Cochran, 1977; McRoberts et al., 2012), the impact of map accuracy may have been greater because incorrect assignment would be more common. Previous research on the effect of map accuracy for post-stratified estimation has focused on the use of classification maps (Czaplewski and Patterson, 2003), which shows that the map accuracy for common classes has a far greater effect on relative efficiency than the accuracy for rare classes. This basic principle could be assumed to apply to the combined effect of continuous variable map accuracy and bin selection, but it has yet to be explored. Regardless, these results show that relatively minor differences in overall model or map accuracy (e.g., ~2% RMSE) have correspondingly minor impacts on the *RE* of post-stratified estimators.

Most of our focus so far has been on comparing *RE* at the statewide level but given that most policy and management decisions happen over smaller extents such as counties, management units, or stands, there has been increasing attention paid to improving estimator precision at these scales (Dettmann et

al., 2022). All the post-stratifications led to a fairly high degree of variability in *RE* across county-level estimation units for both AGB and Forest Area. This was true even for the cover sources that had the highest statewide *RE*, such as *STEM* for AGB, which raises the question of whether overall *RE* at broad extents such as states or regions should be the only target to optimize for. In this study, the number of FIA estimation units with very low *RE* values for a source (i.e., less than 1) was similar for all sources except *GED1c*, but that does not rule out a scenario where a stratification leads to a high statewide *RE* but also produces undesirably low *RE* values in too many estimation units. Therefore, it would be beneficial to also assess variability in *RE* across estimation units, forest types, land ownership, or other groupings when comparing estimation strategies, which is becoming easier to implement with emerging software such as *FIESTA* (Frescino et al., 2022).

The pattern of relative map accuracies between cover sources in specific forest types largely mirrored that of their statewide performance (Figure 9 and Figure 10), with few differences in that pattern between forest types. The notable exception to this is the especially high performance of the ALS-based cover sources in spruce-fir forests, likely because ALS is the best suited for measuring cover when structure is complex and cover is high (Smith et al., 2009). The higher ALS map accuracy in spruce-fir forests did translate to a higher *RE* in forest area estimation, even though ALS had the lowest correlation with forest presence on a plot-level. This reinforces the above conclusion that cover map accuracy may have a significant influence on *RE* when the accuracy improvement or reduction is substantial. Also of note is that the *RE* of estimators for AGB was highest in pinyon-juniper woodlands, whose biomass is more strongly tied to canopy cover than other forest types due to their short stature (Filippelli et al., 2020). This is another example of how correlation between the stratifying variable and forest attribute of interest can determine the *RE* of estimators.

We found that the range in *RE* was substantially different between AGB (1.21 to 1.42) and forest area (1.59 to 3.25) as was the range in plot-level correlations of the cover sources with AGB (0.52 to 0.73) and forest presence (0.74 to 0.83). This contrast is understandable given that plot-level determination of forest presence and ultimately regional estimation of forest area is determined in part by canopy cover measures (Burrill et al., 2024), and thus canopy cover maps would perform better in forest area estimation than AGB estimation or estimation of other height-related structure variables (McRoberts

et al., 2014). This is an extension of the aforementioned importance of the strength relationship between the estimation variable of interest and stratification variable. The combined results of the low effect of map accuracy and strong effect of plot-level variable relationships points to the possible benefit of considering alternative approaches to estimation, such as by choosing auxiliary layers for stratification specific to the variable of interest, using endogenous post-stratification (Breidt and Opsomer, 2008), or considering alternative estimators, like model-assisted estimators, that can better utilize closely related and more accurate auxiliary layers (McRoberts et al., 2014; Myllymäki et al., 2017). For example, canopy height is known to be strongly related to AGB across a wide range of forests (Lefsky et al., 2002), and airborne lidar canopy height maps have proven to be more effective than variables from optical sensors like Landsat for post-stratified estimation of biomass and volume (McRoberts et al., 2012). Our results likewise show that efforts to improve cover map accuracy may be of lower importance for the purpose of post-stratified estimation.

Tree canopy cover mapping, and thus map accuracy, is still important for a variety of other applications, and a major limitation in this endeavor is obtaining consistent reference data for complete spatial and temporal representation. Because of this, we evaluated several combinations of cover reference sources to increase spatial and temporal coverage in terms of their effects on map accuracy and estimator variance. We found that combining sources had little effect on overall model and map accuracy, with accuracy metrics of combinations often being nearly the same as those from their single best source (Figure 12 and Figure 14). This was largely true whether considering the entire dataset, only areas with $\geq 10\%$ cover, or in specific forest types. However, combinations sometimes resulted in higher *RE* than their primary source or either source alone. For example, supplementing the ALS-based sources with *STEM* and *CCLIVE* increased their *RE* in statewide AGB estimators, and combining *STEM* and *CCLIVE* had a synergistic effect of slightly increasing *RE* over using *STEM* alone. We found this often to be the case when looking within specific forest types as well. Thus, increasing sample size and representation of specific areas through combining sources may allow for a better representation of plot conditions in the model that translates to improved estimation, even if the map accuracy statistics are no better. Combining sources to increase coverage for canopy cover modeling is not common practice nor heavily researched, though it is used in the LANDFIRE program (La Puma, 2023). However, efforts have

been undertaken to combine datasets using different field protocols for biomass modeling over large extents (Duncanson et al., 2022; Hudak et al., 2020).

While there have been a number of studies comparing different canopy cover methods (Bunnell and Vales, 1990; Fiala et al., 2006; Ko et al., 2009; Korhonen et al., 2011, 2006; Paletto and Tosi, 2009; Riemann et al., 2016; Smith et al., 2009; Tang et al., 2019), to our knowledge, this study is the first attempt to combine data from the different methods for constructing remote sensing models. We posited that a stronger direct relationship between cover sources would allow them to perform better in combinations for improving map accuracy, but what we found was that the accuracy of most combinations fell between the accuracies of their constituent sources, regardless of their similarity. Even combinations like *LINE*>*DOT*>*CCLIVE*, which had sources with the weakest relationship (*LINE* to *DOT* RMSE = 18.84), did not suffer great mapping performance reductions. This is an indicator that even moderately related cover sources may be combined to increase sample size and coverage for potentially improving structure estimation if not map accuracy.

The above finding could open opportunities for cost saving or model improvements in broad tree canopy cover mapping efforts, such as creation of the NLCD TCC product. The models used to create the TCC product were trained from dot-grid aerial photo-interpretation of nearly all FIA plot locations in a single panel (Heyer et al., 2025), and we used the Colorado sample for our *TCC* variable. We compared the results of *TCC* to *CCLIVE*, which is itself a combination method being comprised ~31% of dot-grid measurements and thus strongly related to *DOT* (RMSE=7.84, slope=0.91, intercept=0.96). *CCLIVE* had slightly higher performance metrics than *TCC* in model and map accuracy. Also, post-stratification with the *CCLIVE* map yielded the highest *RE* for forest area, while *TCC* had the lowest. These results suggest that expanding to a larger sample for model training could be beneficial for cover mapping and developing strata for forest area estimation. Taking this into account in a full cost benefit analysis of ocular field methods versus pre-field dot-grid methods could yield savings for future efforts. Combining data sources and use of *CCLIVE* would also enable a wider temporal representation for both training and testing of the temporal transfer of models (Filippelli et al., 2024); temporal transfer was used in the latest iteration of NLCD TCC production with models trained from nationwide photo-interpretation of NAIP using a single FIA panel (Heyer et al., 2025).

Spaceborne lidar presented an appealing alternative to other sources of canopy cover that could also be obtained at lower cost while providing a large sample with wide spatial coverage and relatively high frequency. We expected the results from GEDI to be similar to those from ALS. However, *GEDIc* had a weak curvilinear relationship to *ALSc*, and it had the lowest model and map accuracies and resulted in the lowest *RE* gains for both forest area and AGB. Factors related to GEDI processing and estimation of cover may explain its poor performance in this study. First, *GEDIc* is dependent on correct separation of ground and aboveground energy returned, which is challenging in slopes of greater than 10° with large footprint lidar (Wang et al., 2019), the topography for much of Colorado. Second, calculating canopy cover also depends on ground and canopy backscattering coefficients which vary spatially (Li et al., 2024). Third, the overall GEDI cover metric (i.e., *GEDIc* in this study) is meant to reflect all vegetation above ground rather than above a typical height threshold like 2 m used to distinguish tree cover from cover due to other vegetation (Tang and Armston, 2019). These factors are likely to introduce much more error into GEDI measurements than ALS, making them correspond less with the true canopy cover and less consistent and thus also more weakly related to Landsat.

While this study highlights the trade-offs and potential combinations of various canopy cover reference sources, several limitations in our comparative approach point toward necessary avenues for future investigation. Cover sources were not universally available on the same set of plots for the same time periods, which complicates the interpretation of some analyses. All the sources, and thus the models, were zero-inflated but to varying degrees, which likely had a strong influence on model performance statistics. All sources could be compared exactly in terms of map accuracy and post-stratified estimators, but simulating varying degrees of zero-inflation in the models could better elucidate its effect on these downstream evaluations. Alternatively, future efforts using the same set of plots may be able to provide more conclusive results with regard to direct comparison of sources and of model accuracy. Some sources may also be modifiable to improve direct comparison, such as removing saplings in the calculation of *STEM*. Also, to better isolate the impact of map accuracy on Relative Efficiency (*RE*), a simulation study could test the effects of purposely degrading cover map accuracy or the cover source used for modeling with noise in a sensitivity analysis. Noting the factors described above that affect GEDI performance, further testing could include using waveform deconvolution to create >2 m

cover metrics, evaluating alternative ground-finding algorithms for steep slopes (Wang et al., 2019), and local calibration of reflectance constants (Li et al., 2024). Given that *RE* gains varied significantly between forest area and biomass estimates in this study, and other studies have also found substantial differences in *RE* between different forest attributes (McRoberts et al., 2012; Schroeder et al., 2022), future work should continue test multiple forest attributes to consider the broader effect of choices in post-stratification. Finally, this study only considers the use of canopy cover maps for post-stratified estimation, as that is the current FIA protocol, but other research has shown promising improvements in estimator precision by considering alternative types of stratifying layers, such as canopy height, or alternative estimators like model-assisted estimators (McRoberts et al., 2012; McRoberts et al., 2014; Myllymäki et al., 2017; Schroeder et al., 2022; Strunk et al., 2019).

6 Conclusion

A wide variety of canopy cover measurement techniques have been used in different places and times, and the lack of consistency and gaps in coverage poses a challenge for remote sensing of canopy cover over broad spatial and temporal extents. This study provides some insight on the relationship between different cover measurements, how they may be used for broader cover mapping with remote sensing, and how those maps may in turn influence the downstream application of post-stratified estimation of forest attributes. We found that most cover sources led to similar enough map accuracies that the differences did not have a strong influence on the precision of post-stratified estimators of forest area or aboveground biomass. The relative efficiency of estimators depended far more on the strength of the plot-level relationship between the cover reference source and the forest attribute of interest, a finding supported by sampling theory. Therefore, efforts to marginally improve generic cover map accuracy may yield diminishing returns for forest inventory estimation precision compared to selecting stratification variables or reference sources that are mechanistically linked to the specific structure attribute being estimated.

Furthermore, our evaluation of data combinations reveals that integrating diverse reference sources can effectively increase spatial and temporal coverage without significantly compromising map accuracy and may in some cases increase estimator precision. Spaceborne lidar from GEDI presented a new and appealing method that could increase the spatial coverage and frequency of cover sampling at

low cost, but it performed poorly in our analysis, possibly due to topographic and metric definition challenges. In contrast, the strong performance of models trained from the mixed-method source *CCLIVE* and the stem mapping derived cover (*STEM*) highlights the value of leveraging existing, cost-effective inventory data for broad-scale mapping. Ultimately, these findings indicate that future post-stratification strategies should prioritize the functional relationship between auxiliary data and target variables over map accuracy alone, and that combining disparate reference datasets offers a viable pathway for large-area canopy cover mapping and forest monitoring.

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CHAPTER 3—Multi-temporal digital aerial photogrammetry to support statewide forest structure estimates and assess post-fire canopy change in the Rocky Mountains

1 Abstract

Multi-temporal digital aerial photogrammetry (DAP) from national imaging programs could enable 3D canopy measurements every 2-3 years to support broad-scale operational forest monitoring objectives such as tracking changes from disturbance, but this valuable source of information has remained unutilized for this purpose. Furthermore, periodically collected DAP could support national forest inventories by improving population estimates for forest attributes related to canopy height such as aboveground biomass. To evaluate these applications, we created statewide canopy height models (CHMs) from multi-temporal DAP using National Agricultural Imagery Program imagery (2019, 2021) across Colorado, USA and compared them to airborne lidar (ALS) CHMs to assess accuracy across scales and forest types, quantify post-fire change, and evaluate the precision of post-stratified estimators of forest structure. At 1 m resolution, DAP explained just over 50% of the variance in ALS height (RMSE = 2.79 m) with minimal bias. Accuracy improved substantially with spatial aggregation, with 90 m mean height and canopy cover metrics closely approaching ALS. Performance was highest in closed-canopy forests and lowest in sparse woodlands. In post-fire environments, DAP produced lower CHM estimates than ALS in moderate and high burn severity, likely due to omission of residual stems, leading to greater apparent loss relative to ALS. Despite these limitations, DAP-based stratification achieved nearly identical precision to ALS for statewide aboveground biomass estimation but was less effective for forest area. These results demonstrate that multi-temporal DAP can support large-area forest monitoring when used with appropriate spatial scales and applications.

2 Introduction

The rapid growth of digital aerial photogrammetry (DAP) has created new opportunities for three-dimensional mapping of forest structure at a substantially lower cost than airborne laser scanning (ALS), yet DAP remains underutilized for monitoring across broad spatial extents. At the same time, forest remote sensing has increasingly shifted towards multi-temporal mapping to support monitoring, disturbance assessment, and reporting (Woodcock et al., 2020). Because much of this monitoring

currently relies on two-dimensional optical and radar backscatter measurements known to saturate in high leaf area index or biomass (Lu, 2006), further integration of three-dimensional canopy measurements is critical for monitoring the full range of aboveground biomass (AGB), volume, and other forest structure attributes (Lefsky et al., 2002). This has motivated the extensive use of ALS and, more recently, sampling spaceborne lidar, which are limited by high cost or discontinuous spatial coverage. DAP represents a potential complement to lidar that could enable more frequently updated, spatially continuous canopy height products over broad regions by utilizing repeat aerial stereo imaging efforts, such as the National Agricultural Imagery Program (NAIP) in the United States. Canopy height products, like those made from NAIP-based DAP, could support a wide range of downstream applications related to forest structure monitoring, including supporting population estimates by national forest inventories and tracking canopy changes related to disturbances.

Accuracies associated with height estimates from DAP have already proven sufficient to make the data an appealing alternative for many applications traditionally reserved for ALS. Numerous studies have shown that DAP-derived height metrics can be used to model forest structure attributes such as AGB with an area-based approach, often with performance comparable to ALS (White et al., 2013). Consequently, DAP has been applied to a growing range of forest monitoring tasks, including detection of insect damage (Shrestha et al., 2024), forest height growth modeling (Janiec et al., 2024), and estimation of canopy cover and LAI (Li et al., 2022).

While these research applications have expanded, substantial gaps remain in our understanding of DAP usage in operational, broad-scale contexts. Much of the recent validation and methodological development has focused on low-flying uncrewed aerial vehicles (UAVs) that capture ultra-high-resolution images (Iglhaut et al., 2019). Comparatively less attention has been given to DAP products obtained with traditional airborne or satellite platforms of lower resolution covering large extents, leaving many previously identified research gaps unaddressed (Goodbody et al., 2019). As a result, questions remain regarding the sensitivity of DAP-derived canopy height to sensor type (e.g., frame versus pushbroom sensors) and acquisition parameters like ground sampling distance, image overlap, and viewing geometry. Furthermore, many studies have been limited to small extents and a narrow range of forest

conditions, leaving uncertainty about DAP performance across forest types with contrasting structure and canopy architecture.

Hesitancy to adopt DAP for broad-scale forest applications may also stem from perceived trade-offs and limitations relative to ALS. A key constraint is DAP's reliance on an external digital terrain model (DTM) for accurate height normalization, although this limitation has been substantially reduced by the availability of accurate high-resolution DTMs across most of the United States through the 3D Elevation Program (Stoker and Miller, 2022) and in many other regions globally. DAP-derived canopy heights are also known to exhibit an envelope effect, failing to capture interior structure and small gaps, and they show systematic negative bias compared to ALS (White et al., 2013). However, DAP is commonly acquired during leaf-on conditions, whereas ALS is often acquired during leaf-off for terrain mapping, which can systematically underestimate canopy height in certain forest types (Wasser et al., 2013). While the limitations with DAP may be critical for applications requiring precise treetop heights and individual crown mapping, they may be less consequential when canopy height models and other metrics are aggregated to coarser spatial resolutions for broad-scale applications.

One specific area where these broad-scale operational gaps are most evident is in the characterization of forest change. This is particularly relevant as the area of forest fires in the western United States are projected to increase under climate change (Abatzoglou et al., 2021). Remote sensing has traditionally relied on spectral change indices (e.g., dNBR) that may be related to fire effects but do not directly measure structural loss (Hudak et al., 2007). While multi-temporal ALS can capture forest structure loss effectively (Hudak et al., 2012; Wulder et al., 2009), the rarity of coincident pre- and post-disturbance collections limits its operational use. In contrast, the frequent revisit of national imaging programs like NAIP could enable pre- and post- canopy height mapping with DAP for most disturbances. However, the few studies of disturbance incorporating DAP have either been conducted with a UAV over small extents or used DAP for only one time period (Batchelor et al., 2025; Frank et al., 2025; Goodbody et al., 2018; Ota et al., 2019; Reilly et al., 2021). To our knowledge, no research has used multi-temporal DAP from conventional aircraft to quantify canopy changes related to disturbance over broad extents.

DAP also has substantial potential to support national forest inventories such as the U.S. Forest Inventory and Analysis (FIA) program in making population estimates of forest structure attributes. FIA

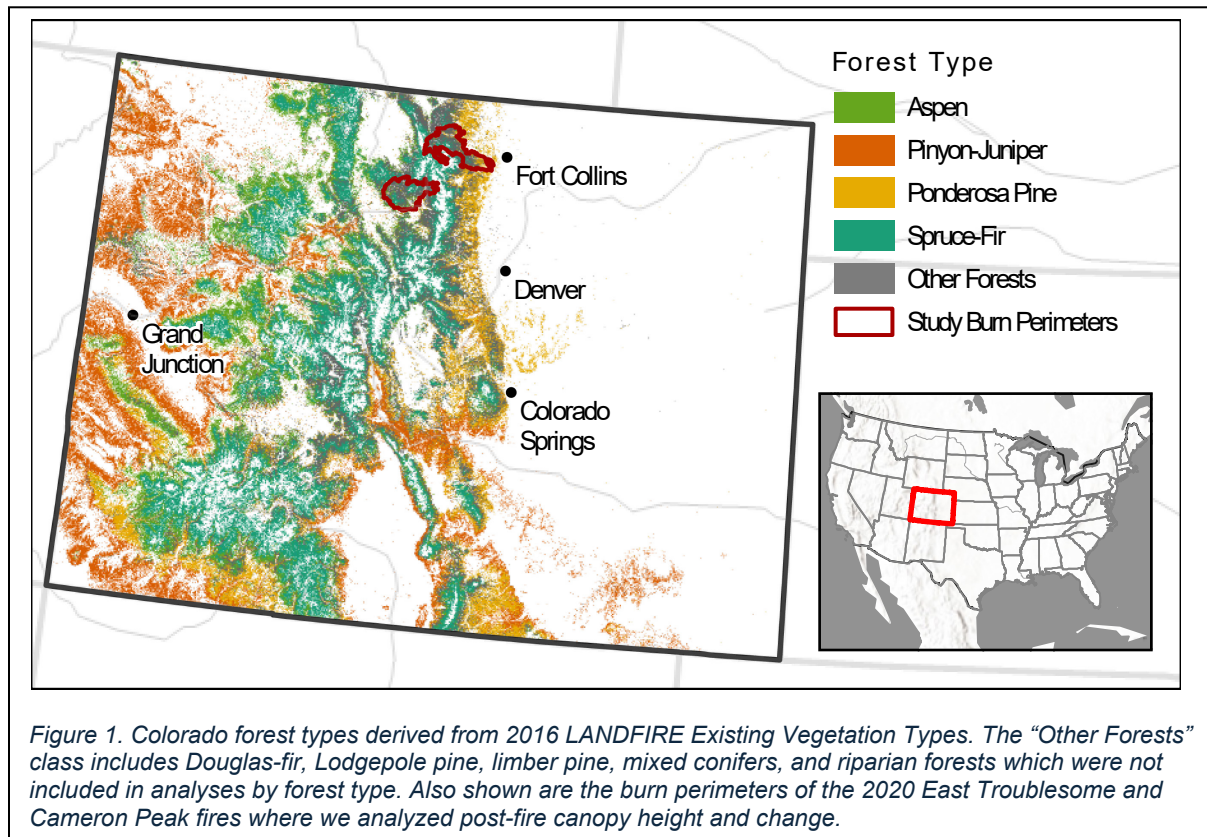
currently relies on Landsat-based tree canopy cover maps for post-stratified estimation for forest attributes like forest area and AGB (Heyman et al., 2025; Westfall et al., 2021). While canopy cover is particularly effective at improving the precision of forest area estimators (McRoberts et al., 2014), canopy height serves as a better stratification variable for other structure attributes such as volume or biomass (McRoberts et al., 2012). A national high-resolution canopy height product developed from DAP may be a feasible alternative to support these estimation frameworks, especially since post-stratified estimation requires average height information at the plot scale, possibly mitigating DAP's canopy envelope limitations. Previous research has demonstrated this feasibility in specific regions, with studies showing that inclusion of DAP-based layers can improve the precision of post-stratified estimators (i.e., gain in efficiency) by up to 24% for forest area and 46% for forest volume over using canopy cover maps and by up to 305% for forest area, 187% for volume, and 316% for yield over using a simple random sample (Cao et al., 2025, 2022; Pulkkinen et al., 2018; Schroeder et al., 2022; Strunk et al., 2019). Unfortunately, none of these studies compared the precision of DAP stratification directly against ALS, which is considered the benchmark for remotely sensed canopy height. Detailed analyses comparing DAP and ALS for making population estimates across diverse regions and forest types are needed to evaluate operational benefits at broad extents, including county, state, and even national scales.

The overarching goal of this study is to investigate the operational use of multi-temporal DAP over broad extents for mapping canopy height and change for supporting national forest inventories. We approach this goal from the perspective of a hypothetical scenario where statewide high-resolution canopy height models (CHMs) could be produced from NAIP every 2-3 years to support forestry applications in the United States. Specifically, we compare these high-resolution DAP CHMs against ALS CHMs in Rocky Mountain forest types and in burn areas to understand DAP's height accuracy and its ability to improve the precision of forest structure population estimates over areas of interest. A combination of ALS collections across multiple years and NAIP pushbroom imagery in 2019 and 2021 covering the entire state of Colorado enabled us to answer the following questions:

1. What is the accuracy of canopy height maps from DAP as compared to ALS, and how does this vary by scale and forest type?

2. How does post-fire canopy height and change in canopy height from DAP compare to ALS across different burn severities?
3. What are the precisions of post-stratified estimators of forest area and AGB when using DAP or ALS CHMs as stratifying layers, and how does this vary by scale and by forest type?

This study will be the first to our knowledge to evaluate broad-scale multi-temporal DAP in wildfire applications and to compare the relative efficiency of DAP and ALS canopy height products for post-stratified estimation of forest structure.



3 Methods

3.1 Study Area

The state of Colorado encompasses diverse climatic conditions and topographic gradients, resulting in highly varied forest structures and compositions (Figure). The forest types and dominant species in Colorado differ in their crown architecture and the spatial distribution of individual trees, which is likely to affect canopy height measurement accuracies from ALS and DAP. The southern Rocky Mountains dominate the state's central corridor, where mid-elevation montane forests are primarily composed of

aspen (15.3%), Douglas-fir (6.7%), and ponderosa pine (6.3%) (USDA Forest Service, 2023). Mature ponderosa pines typically develop broad, flat tops and grow in relatively open stand configurations. Aspen stands feature rounded, contiguous canopies, while Douglas-fir exhibit deep, dense, and conical crowns. Ascending into the subalpine zone, the landscape transitions heavily to spruce-fir (20.8%) and lodgepole pine (6.2%) forests (USDA Forest Service, 2023). Spruce and fir species are characterized by highly conical crowns with very narrow, sharply pointed terminal leaders. In contrast, lodgepole pines possess narrow, cylindrical crowns and frequently grow in dense homogeneous even-aged stands. The arid western portion of the state, characterized by the Colorado Plateau, contains abundant sparse, short-stature pinyon-juniper woodlands (28.3% of forested area) (USDA Forest Service, 2023). Pinyon and juniper trees possess irregular, bushy, and rounded structures distributed with very low canopy cover. Finally, the eastern plains consist largely of agricultural fields and shortgrass prairie, with tree cover restricted mainly to riparian cottonwood corridors (0.5% of forest cover) that feature massive, broad, and spreading crowns (USDA Forest Service, 2023).

To specifically evaluate the performance of DAP and ALS in post-fire environments, analyses were conducted within the burn perimeters of the 2020 Cameron Peak (845 km²) and East Troublesome (766 km²) fires in northern Colorado (USFS/USGS, 2022). These historically large wildfires burned across complex, steep topography predominantly covered by lodgepole pine and spruce-fir forests. The events created a heterogeneous mosaic of canopy disturbance, providing an ideal setting to test post-fire canopy height models and change. The distribution of burn severities across the full extent of both burn areas consisted of 17.1% unburned or very low severity, 22.5% low severity, 27.9% moderate severity, and 31.8% high severity according to the classified difference Normalized Burn Ratio (dNBR) from Monitoring Trends in Burn Severity (USFS/USGS, 2022). Post-fire analyses were restricted to the area with post-fire ALS available (1193 km²) and change analyses were restricted to areas with both pre-fire and post-fire ALS coverage (640 km²).

3.2 Airborne Laser Scanning (ALS)

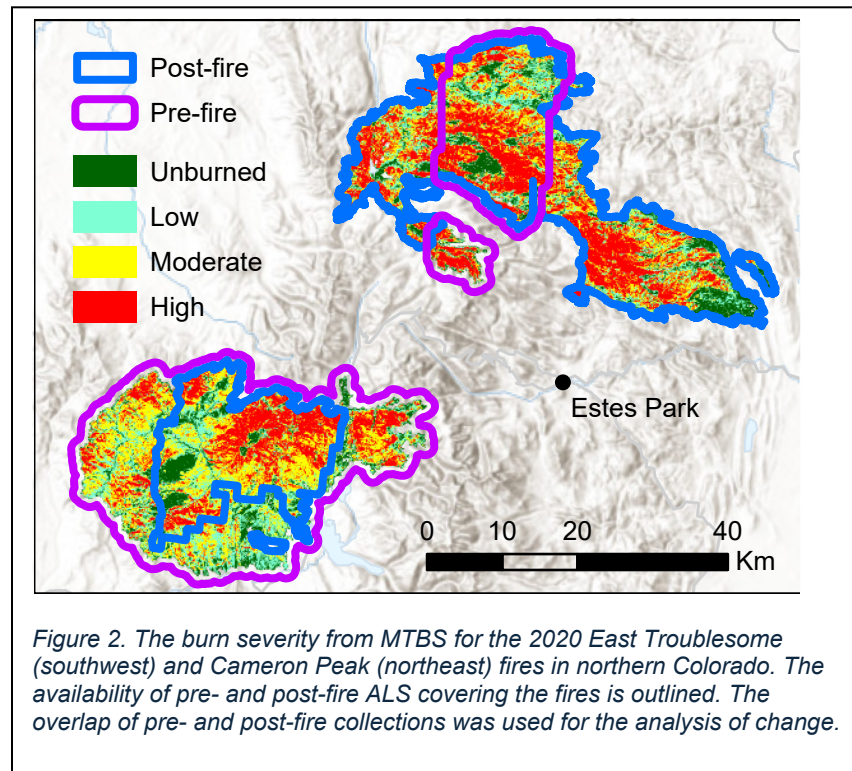
Canopy height models were created from the point clouds of 57 ALS collections covering the entire state of Colorado from 2010 to 2023. The collections were obtained primarily from a combination of the 3D Elevation Program (Stoker and Miller, 2022) and Colorado Hazard Mapping Lidar Portal (Colorado

Water Conservation Board, n.d.). Transformation of all collections to an Albers Conic Equal Area projection and NAD83 (2011) datum was performed with the Point Data Abstraction Library (PDAL Contributors, 2022) and all other point cloud processing was performed with lasR (Roussel, 2026). Ground classification of the points was completed by the vendor and available for every point cloud. For each collection, a Triangulated Irregular Network (TIN) was constructed from the ground points and then rasterized create a 1 m resolution Digital Terrain Model (DTM) that was used to height normalize the points. Classification and removal of noise with the Statistical Outlier Removal algorithm (Rusu et al., 2008) was applied to a collection only if the initial CHM showed a high degree of remaining noise not classified by the vendor. Points classified as noise or exceeding -5 to 50 m in height were excluded, and the remaining points were filtered with a 1 m grid keeping the highest point. The filtered points were used to create a 1 m resolution CHM using the pit-free algorithm (Khosravipour et al., 2014) by taking the maximum pixel value from rasterized TINs made from points above 0, 2, 5, 10, and 15 m with a maximum edge length of 2 m for all but the first layer.

The individual collection DTMs and CHMs were mosaiced to support the statewide and burn area analyses. A 1 m CHM was created for the state to most closely reflect the conditions in summer of 2019 when aerial imagery was collected for the DAP point cloud. Collections were mosaiced with preference for those closest in time to the 2019 DAP collection but without an intervening fire between the ALS and DAP by using burn perimeters from MTBS (USFS/USGS, 2022). The 1 m DTM was similarly mosaiced for height normalization of the DAP point clouds. For the fire-related analyses, the CHMs from the ALS collections within 3 years of the 2020 fires were mosaiced; collections after the fires were used for the post-fire analysis and the overlap area of collections before and after the fire were used for the change analysis.

A series of masks were created to set the mosaiced CHM height to zero for water, buildings, crops, and cliffs. The water mask was created from the waterbody layer of the 3D Hydrography program dataset (U.S. Geological Survey, 2025). Crops were masked using the cultivated layer from the 2023 Cropland Data Layer (USDA-NASS, 2024), which is based on a crop classification of the prior five years. Buildings were masked using the 2018 Microsoft Buildings polygons (Microsoft, 2018). There were errors in ground classification at the top of cliffs that led to gross overestimates of canopy height near virtually all cliffs,

which cover much of the landscape in the canyonlands and mountains of Colorado. To reduce the extent of these errors we also created a cliff mask based on areas with greater than a 60 degree slope derived from the 1 m DTM. This combination of masks reduced much of the overestimates of canopy height in both the ALS and DAP CHMs.



3.3 Digital Aerial Photogrammetry (DAP)

CHMs were created from DAP point clouds for comparison to the ALS CHMs. Stereo aerial imagery with a 0.6 m resolution was collected in 2019 and 2021 across all of Colorado for the National Agricultural Imagery Program (NAIP). NAIP images are collected every 2-3 years, mostly in the summer, in each state to create a statewide orthomosaic, but the original stereo images are rarely made available or used to create a point cloud or elevation model. In this case, the vendor collected data with the Leica ADS100 pushbroom instrument which has forward (25.6°), nadir (0°), and backward (19.4°) looking sensors. The vendor used the nadir and backward looks to create DAP point clouds attributed with near-infrared, red, and green reflectance values for each flightline with the Leica Xpro software, which uses a proprietary variant of the semi-global matching algorithm (Hirschmuller, 2008). The 2019 and 2021 DAP point clouds were processed similarly to the ALS point clouds with PDAL (PDAL Contributors, 2022) and lasR

(Roussel, 2026), including reprojection, height normalization with the ALS 1 m DTM, noise classification with the Statistical Outlier Removal algorithm (Rusu et al., 2008), filtering for non-noise points between -5 and 50 m, and creation of a 1 m CHM with the pit-free algorithm (Khosravipour et al., 2014). The DAP point clouds often had a high level of error in dark topographic shadows, which were most common downhill from cliff lines. To reduce the extent of these errors while retaining legitimate canopy height measurements, we made a 50 m downhill buffer of the cliff mask described in section 3.2, and any points within this buffer that had an NDVI of less than -0.3 were set to a canopy height of zero before CHM creation.

We created statewide 2019 and 2021 1 m CHM mosaics for the DAP and applied the same series of masks that were used for the ALS CHMs (section 3.2). The 2019 pre-fire and 2021 post-fire DAP CHMs were simply an extract of the statewide datasets over the burn areas.

3.4 Canopy Height Model (CHM) comparisons

We compared the DAP CHMs to the ALS CHMs in multiple ways to better understand the contexts in which a statewide 1 m DAP CHM product would be an acceptable alternative to ALS. In these comparisons, the ALS CHMs are treated as the reference standard because of their well-established height accuracy, though all methods of canopy height measurement are subject to some error. At the statewide level, the 2019 DAP CHM was compared to the circa 2019 ALS CHM mosaic across scales and by forest type.

For evaluating the effect of scale, we spatially aggregated the high-resolution CHMs with different resampling methods to multiple resolutions and made comparisons between ALS and DAP for each resulting layer. The 1 m CHMs were resampled to 10 m, 30 m, and 90 m resolutions using the *mean*, the 50th, 75th, 80th, 85th, 90th, 95th, and 100th percentiles (*p50*, *p75*, etc.), and the percent of pixels with a height greater than or equal to 2 m (*c2*) and 5 m (*c5*). The *c2* and *c5* metrics reflect CHM-based canopy cover with height thresholds that are commonly used to define forest. The 10 m resolution reflects the scale of the high-resolution Sentinel-2 and planned Landsat Next bands, and it is closer to the size of an FIA subplot which has a 14.63 m diameter. A 30 m resolution matches the scale of a Landsat 4-9 pixel, which was also the data source used for creating the forest type and burn severity maps used for some of

the analyses. The 90 m resolution matches the size of a 3x3 window of Landsat pixels and is closer in size to an FIA plot which has an 87.78 m diameter.

For the analysis by forest type, we reclassified the 2016 LANDFIRE Existing Vegetation Type (EVT) groups as described in Table S 3 of the appendix and focused on four of the most prevalent forest types in Colorado as defined by their dominant species: aspen (15.5%), pinyon-juniper (26.0%), ponderosa pine (14.6%), and spruce-fir (24.4%). These forest types also have notable differences in their crown architecture and spatial distribution as described in section 3.1, which makes them excellent candidates for testing the accuracy of DAP CHMs in different forest contexts.

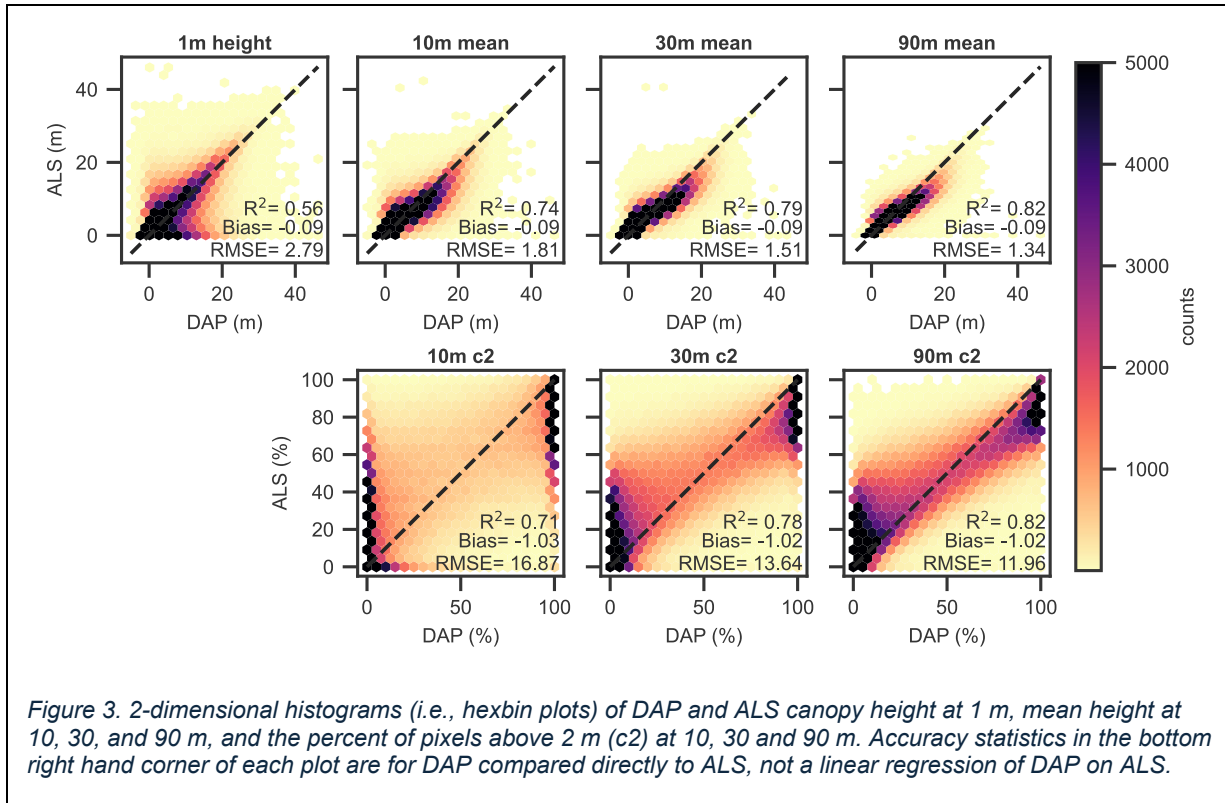
Multi-temporal lidar is an effective tool for evaluating forest structure change following disturbances like fire, but it is rarely available. Because of the potential of aerial stereo image collections to more often capture these events with their broader coverage at higher temporal frequencies, we also compared DAP CHMs against ALS in post-fire environments and compared bi-temporal DAP and ALS for measuring change in canopy height. These analyses were conducted in areas of the 2020 Cameron Peak and East Troublesome fires (section 3.1; Figure 2) where there was recent ALS pre- and post-fire coverage. The accuracy of the 2021 post-fire DAP CHMs at 1 m resolution was compared to post-fire ALS by MTBS burn severity class (USFS/USGS, 2022). We also compared the DAP and ALS measurements of change in 1 m canopy height by burn severity class.

All evaluations of the DAP CHMs against ALS were conducted using the same approach. A systematic sample was used for computational efficiency. For the statewide analyses, the sample spacing was 450 m in both directions, and each sample point was in the center of the 90 m resolution pixels ($n = 1.33$ million). In the analysis by forest type, a sample unit was only retained if the 90 m block was of the same forest type to reduce the effect of possible misclassification errors and speckle in the EVT map ($n = 152,718$ for the four forest types). For the fire analyses, the sample spacing was 30 m with points located in the center of the burn severity class pixels ($n = 1.32$ million for post-fire and $n = 713,101$ for change). Comparisons of DAP to ALS were made by plotting the canopy height measurements against each other and by calculating the root mean squared error (RMSE), coefficient of determination (R^2), and mean of the residuals (bias).

3.5 Post-stratified estimation of forest structure

We tested the efficacy of a DAP CHM product to create stratification layers for post-stratified estimation of forest area and aboveground biomass (AGB) as one of the primary applications it could be used for. Because the best stratification variable is one that is linearly related to the variable of interest (Cochran, 1977), we examined the correlation of plot-level proportion of forest area and plot-level AGB with the different 90 m resampling metrics of the 2019 DAP and ALS CHMs to decide which metrics should be used as the stratification layers. The 90 m resolution was used because it most closely matches the diameter of FIA plots. To bin and create strata from the continuous height or cover metrics we extracted the splits from Classification and Regression Tree (CART) models between the forest attributes and the selected layers. This approach has been effective in post-stratification (Myllymäki et al., 2017; Pulkkinen et al., 2018) as the objective of CART is to find the divisions in the predictors that minimize variance in predicting the response variable.

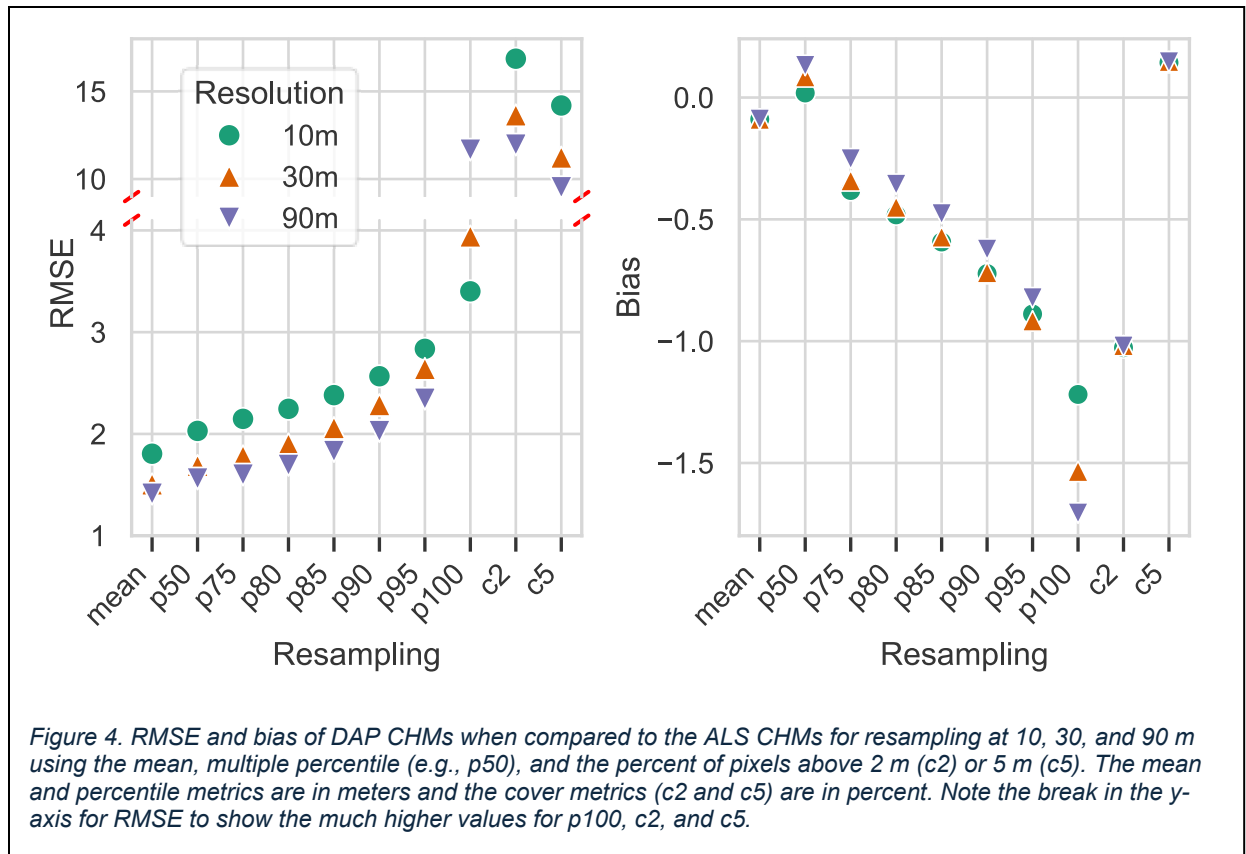
With the stratification layers and FIA data, we created circa 2019 post-stratified estimators of forest area and AGB for the state and county-level estimation units and by forest type. For the forest type analysis, we focused on the FIA forest type groups (i.e., FORTYPECD) that corresponded to the pinyon-juniper, spruce-fir, ponderosa pine, and aspen forest types used in the CHM comparison (section 3.4). The strata were extracted for each FIA plot in the 2019 Colorado evaluation group (i.e., EVALID=081901) at the true plot locations. The mean and variance of post-stratified estimators for the estimation units in each level (i.e., state, county, forest type groups) were obtained with the Green Book area estimator for forest area and the ratio estimator for AGB in FIESTA (v3.6.4). Estimation units and strata were combined where necessary to obtain at least 10 plots per estimation unit and 2 plots per strata. We compared the relative efficiency (RE) of the estimators using the DAP and ALS stratifications to the variance of estimators (V) using a simple random sample (SRS) for evaluating their effectiveness in improving precision (i.e., $RE = \frac{V_{SRS}}{V_{test}}$). RE values less than one indicate a loss in precision relative to using an SRS for estimation, and values greater than one indicate a gain in precision.



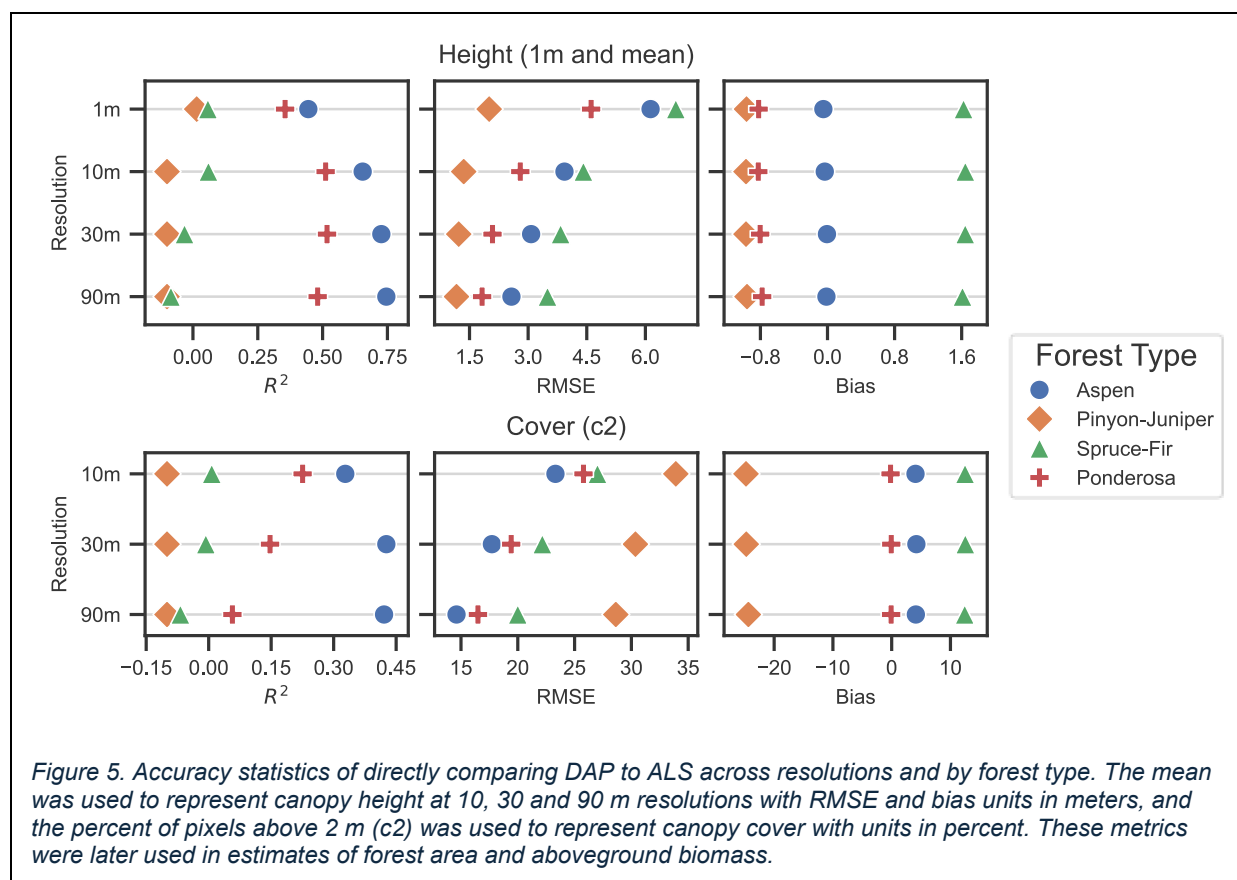
4 Results

4.1 Statewide Canopy Height

At the 1 m native resolution, DAP measurements explained just over 50% of the variance in ALS canopy height, with an RMSE of 2.79 m (Figure 3). DAP heights exhibited a wider spread of errors at lower values but aligned more closely with the 1:1 line at higher values. Because the *mean* and *c2* metrics were selected for stratification, we examined their bivariate distributions, finding that spatial aggregation improved DAP-ALS correspondence. Aggregating to a 90 m resolution with the mean increased R^2 by 0.26 and decreased RMSE by 1.45 m. This improvement was primarily driven by low-value predictions converging toward the 1:1 line, while the overall bias remained stable across all resolutions. The canopy cover metric (*c2*) exhibited a similar scaling response, maintaining a stable bias while R^2 improved by 0.11 and RMSE decreased by 4.91 when going to the 90 m scale. Furthermore, the tendency for fine-resolution DAP *c2* to concentrate heavily at the extremes of 0% and 100% moderated significantly as spatial resolution coarsened.



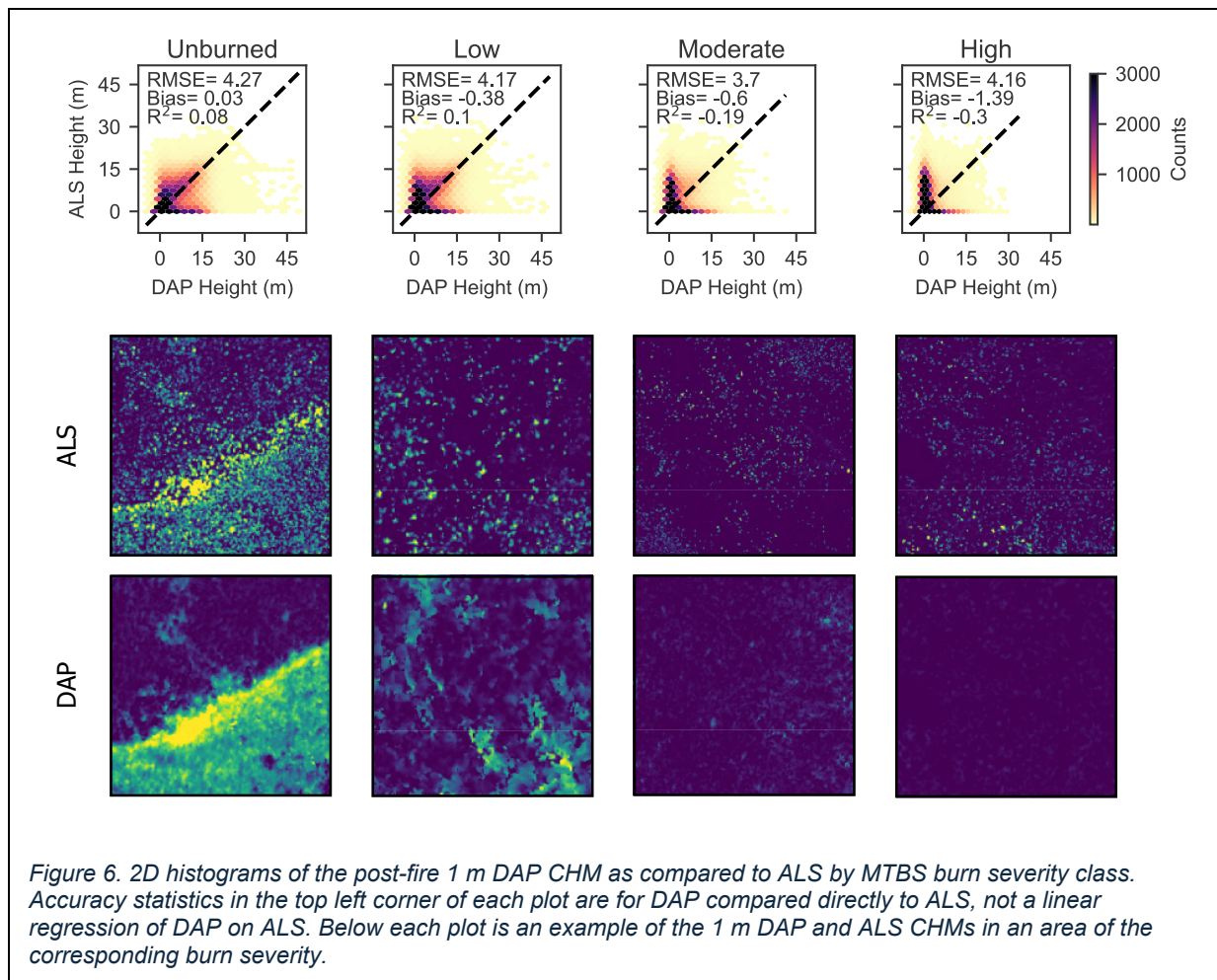
Evaluation of additional height and cover metrics showed similar scale-dependent patterns (Figure 4). Across height metrics from the mean to the 95th percentile, RMSE increased with percentile but generally decreased as spatial resolution became coarser. In contrast, the maximum height metric (*p100*) showed substantially higher RMSE and increasing error at coarser resolutions, likely because of larger aggregations of *p100* being more likely to capture noise in the 1 m DAP CHM. The mean and median height metrics had near-zero bias across resolutions, whereas absolute bias increased slightly for higher percentiles. Overall, DAP height estimates showed a minor tendency to underestimate ALS height for most metrics. Canopy cover metrics showed comparable scale effects with both *c2* and *c5* exhibiting improved agreement with ALS at coarser resolutions while maintaining relatively consistent bias.



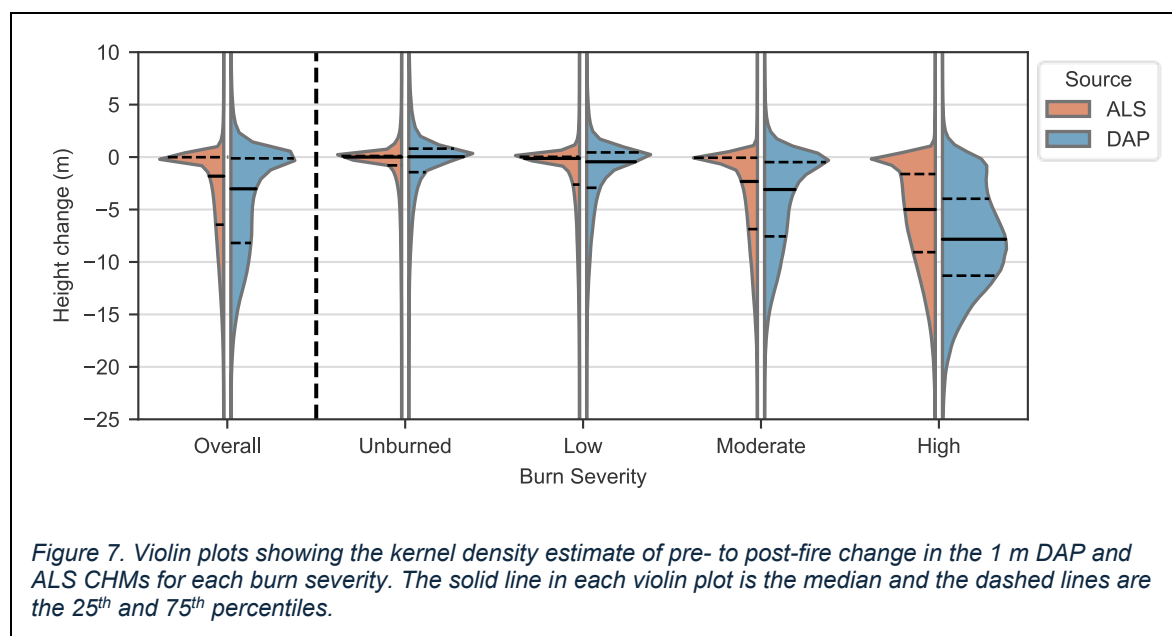
When analyzed by forest type at the 1 m scale, inherent height variability strongly influenced DAP accuracy. Aspen exhibited the highest explained variance and lowest bias, but also the second-highest RMSE, reflecting its high natural variability (ALS standard deviation = 8.23 m). In contrast, pinyon-juniper woodlands had the lowest overall RMSE but negligible explained variance, a result of the exceptionally low height variation in this forest type (ALS standard deviation = 2.02 m). Bias in DAP height followed distinct patterns: pinyon-juniper and ponderosa pine were generally underestimated, whereas spruce-fir heights were overestimated. The relative ranking of forest types by accuracy metrics remained consistent across spatial resolutions, and aggregation improved RMSE for all forest types but by differing degrees. Patterns for canopy cover (c2) by forest type were broadly similar. The ordering of forest types for c2 R^2 and bias was consistent with that observed for height but had a different order for RMSE. Aspen forests had the lowest RMSE for c2, whereas pinyon-juniper woodlands had the highest. In fact, DAP estimates of canopy cover in pinyon-juniper performed worse than a simple mean prediction (negative R^2) and showed very high RMSE and strong underestimation across spatial scales.

4.2 Burn Area Canopy Height

Visually, the post-fire DAP CHM measures trees in unburned areas and misses trees in high severity burns as we would expect, but this pattern is not reflected by a trend in RMSE across burn severities. In unburned areas, DAP effectively captures dense stands but frequently misses trees in sparse stands, which is consistent with our 2019 observations outside burn perimeters. However, the accuracy statistics in unburned areas (RMSE = 4.27 m, $R^2 = 0.08$) are substantially worse than the 2019 1 m accuracies (Figure 3), likely because some MTBS-classified unburned regions actually exhibit apparent tree loss in the post-fire ALS CHM. Furthermore, as burn severity increases, residual stems clearly visible in ALS are largely omitted by DAP. While RMSE does not consistently reflect this omission (fluctuating between 3.70 m and 4.17 m), declining correspondence between DAP and ALS is evident in the progressively negative bias (dropping from 0.03 m to -1.39 m) and a corresponding decrease into negative R^2 values.

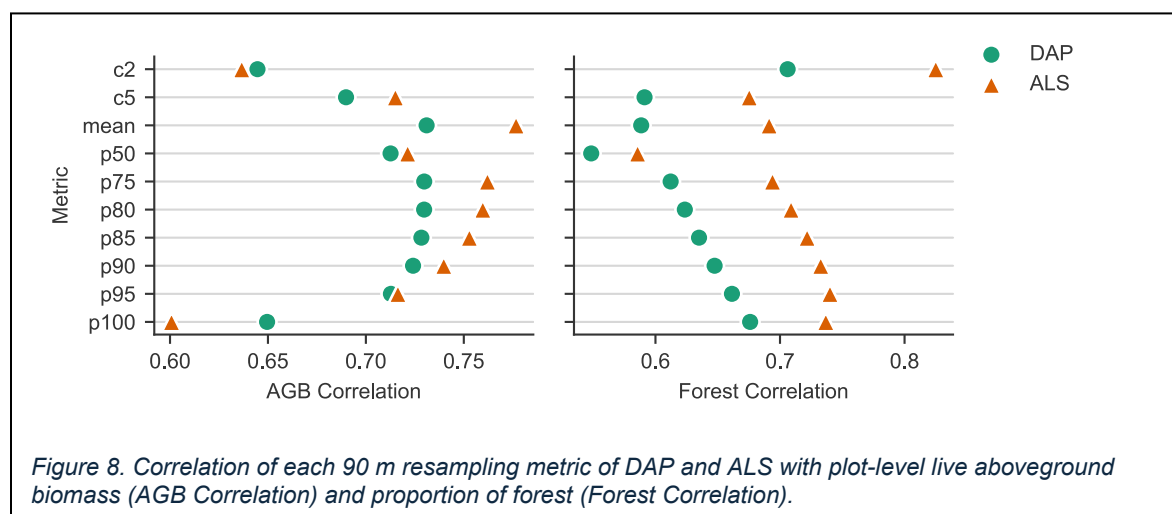


The distributions of overall change in canopy height across the full burn areas for ALS and DAP both had modes near zero (Figure 7), but DAP had a lower median and fatter right tail indicating a greater area with substantial loss in canopy height. The DAP and ALS distributions were most similar in unburned and low burn severity areas, though the DAP distribution has a wider spread around zero, including many positive values, likely because of lower measurement accuracy in general. DAP's greater area with large decreases in canopy height become more apparent in moderate burn severities. In high burn severity, the median loss in canopy height is 2.83 m lower than that of ALS, and its mode is near the median of -7.83 m while the ALS mode is still near zero.

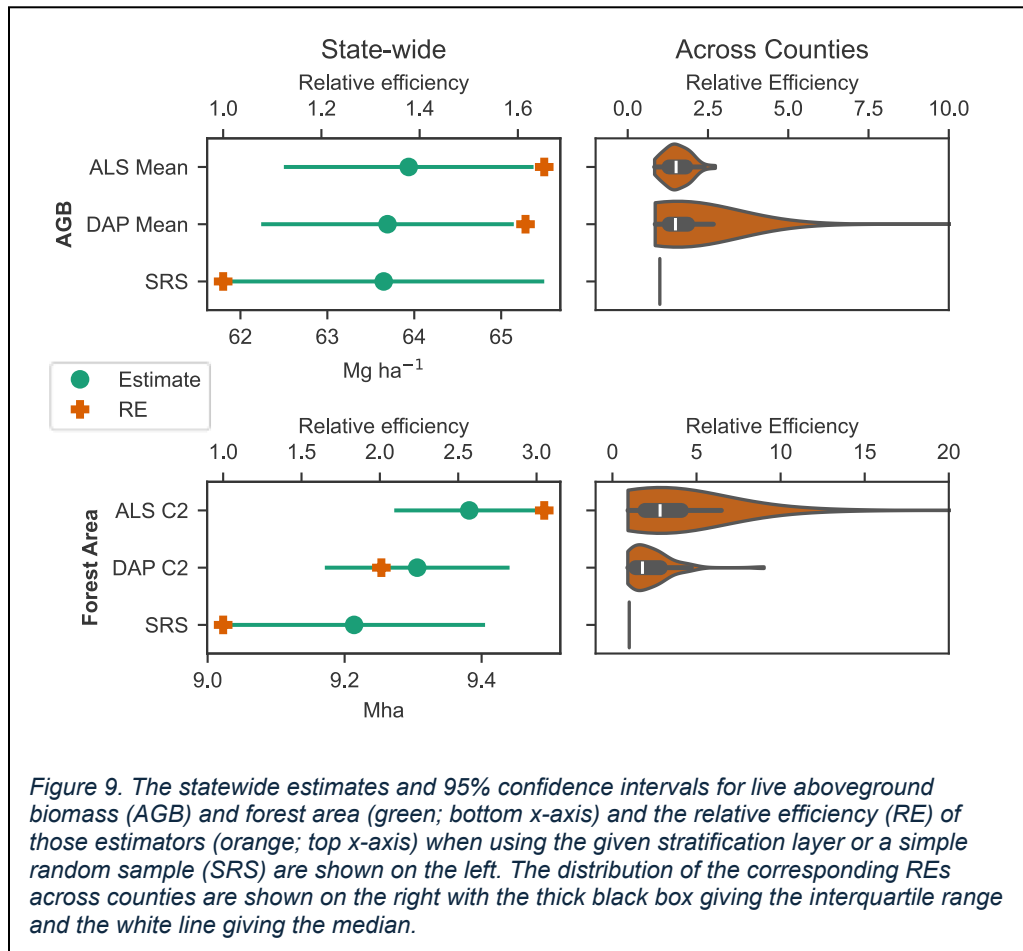


4.3 Estimation of Forest Structure

To select layers for stratification, we examined the correlation of each resampling method with AGB and the proportion of forest area using the 90 m layers, which approximately matches the coverage of an FIA plot. ALS was more strongly correlated to the forest structure variables for nearly all metrics, with an average increase in r of 0.082 for proportion of forest and an average increase of 0.013 for AGB when compared to DAP. For both DAP and ALS, *mean* height was most strongly correlated to AGB (DAP $r = 0.73$, ALS $r = 0.78$), and *c2* was most strongly correlated to proportion of forest (DAP $r = 0.71$, ALS $r = 0.83$).

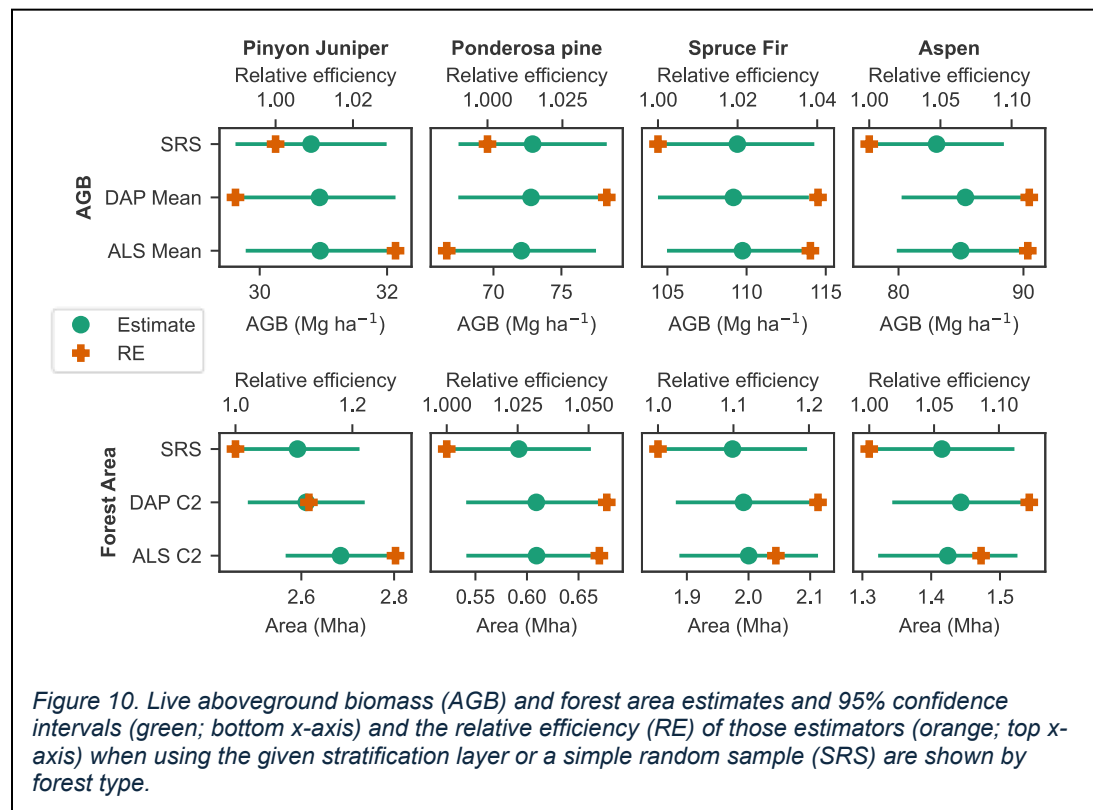


Post-stratified estimation with ALS and DAP substantially improved the precision of estimates for both AGB and forest area at the state and county-levels (Figure 9). For AGB, DAP yielded nearly the same *RE* as ALS at the state level (DAP *RE*=1.62, ALS *RE* = 1.65) and had a very similar distribution across counties, with the interquartile of *RE* being 1.29 to 1.87 for DAP and 1.29 to 1.81 for ALS. For forest area, ALS yielded a much higher *RE* (3.05) than DAP (2.01) at the state level. The distribution of *RE* across counties for ALS was also wider and shifted to the right (ALS *RE* median = 2.83, IQR = 2.16) in comparison to the DAP distribution (*RE* median = 1.79, IQR = 1.47).



The *RE*s from post-stratified estimation for individual forest types (Figure 10) were at most 1.27 and not nearly as high as at the state-level or across counties (Figure 9), which suggests that the primary benefit of stratification was separating forest and non-forest rather than vastly improving estimation within these forest types. For AGB, all *RE*s were 1±0.11 and in some forest types the DAP and ALS *RE*s were

slightly less than 1. Post-stratified estimation with DAP and ALS did improve the precision of forest area estimates for all forest types, though DAP outperformed ALS in all forest types but Pinyon-Juniper.



5 Discussion

5.1 General Agreement and Scale Dependency

This study demonstrates that multi-temporal digital aerial photogrammetry (DAP) derived from operational aerial image programs can support broad-scale forest structure mapping and inventory applications, but with important scale- and context-dependent limitations. Across Colorado, 1 m resolution DAP canopy height models (CHMs) showed moderate agreement with airborne laser scanning (ALS) at fine spatial resolutions, explaining just over half of the variance with an RMSE of 2.79 m and near-zero bias (Figure 3). These results are consistent with prior studies documenting systematic height underestimation in DAP datasets and fall within the wide range of 0.78 to 9.41 m RMSE reported depending on collection parameters and forest context (Dietmaier et al., 2019; Mielcarek et al., 2020; White et al., 2018).

However, a key finding of this research is the strong improvement in correspondence observed with spatial aggregation, which highlights that many of DAP's pixel-level limitations diminish substantially at scales relevant to most forest inventory and monitoring applications. At a 90 m resolution, DAP-derived mean height and canopy cover approached ALS in both bias and explanatory power, with R^2 increasing by 0.26 and RMSE decreasing by 1.45 m for mean height. This confirms the hypothesis that the "canopy envelope" effect inherent to DAP becomes less consequential when metrics are aggregated to plot or landscape scales. This aligns with previous work showing that DAP-derived metrics can nearly match the performance of ALS in area-based modeling frameworks across most regions, including forests of the Rocky Mountains (Filippelli et al., 2019; Goodbody et al., 2019).

5.2 Canopy Metrics and Estimation

The scale-dependent improvement in DAP accuracy directly translated into comparable performance for population estimates of aboveground biomass (AGB) when compared to ALS baselines. We found that resampled DAP and ALS CHMs were most closely correlated when using mean height, rather than higher percentiles, converging toward a 1:1 relationship across the full range of values. This represents a slight contrast to other studies—including prior research in northern Colorado specifically (Filippelli et al., 2019)—which often identify plot-level upper percentile metrics of the point cloud as the most strongly correlated (Goodbody et al., 2021; Strunk et al., 2020). Fortunately, mean height was also the most strongly correlated to AGB in our study, making it the optimal variable for post-stratified estimation.

Despite slightly weaker correlations with AGB ($r = 0.73$ for DAP versus 0.78 for ALS), this difference translated into only a minor reduction in estimator precision. At the statewide level, the *RE* of DAP-based stratification for AGB ($RE = 1.62$) was only marginally lower than that of ALS ($RE = 1.65$), representing a difference of just 1.8%. Furthermore, the county-level distributions of *RE* were nearly identical. Previous work has demonstrated substantial efficiency gains when using DAP to support population estimates in specific regions. For instance, post-stratified estimation of forest yield in Washington state using pushbroom DAP improved precision three- to four-fold over a simple random sample (Strunk et al., 2019). In the southeastern US, DAP led to improvements in the precision of forest volume estimates by 19-30% with area-level Fay-Harriot estimators (Cao et al., 2022) and increased precision by 31% on average in comparison to using canopy cover strata in post-stratified estimators (Schroeder et al., 2022). National-

scale demonstrations in Switzerland showed DAP improved the precision of forest area and growing-stock volume estimators by 34% to 86% (Pulkkinen et al., 2018). Together, our comparative findings and the existing literature indicate that DAP serves as a highly suitable, frequently updated alternative to ALS and canopy cover maps for the post-stratified estimation of height-related variables like AGB and volume.

Given the use of canopy cover for post-stratified estimation of forest area in previous research and operational use in the U.S (Chapter 2; McRoberts et al., 2014; Westfall et al., 2021), we evaluated canopy cover metrics (*c2* and *c5*) derived from the 1 m canopy height products, which did prove to be the most strongly related to forest area. However, the relationship between ALS and DAP *c2* was highly sensitive to resampling resolution, with DAP's ability to estimate intermediate values of canopy cover increasing at lower resolutions. At 30 to 90 m resolutions, its accuracy becomes comparable to Landsat model estimates of ALS-based canopy cover (Chapter 2).

However, even this level of error translated into a weaker correlation with plot-level forest proportion and much lower relative efficiency for estimating forest area compared to ALS (i.e., statewide DAP $RE=2.01$, ALS $RE=3.05$). By comparison, Filippelli et al. (Chapter 2) found that Landsat-based models of canopy cover in Colorado could achieve a RE of up to 3.25. Schroeder et al. (2022), also found that Landsat-based canopy cover generally served as a better stratification layer for forest area than DAP in the southeastern US. Considering the modest performance of DAP for this application, cover maps derived from other optical and SAR sources may remain preferable for forest area estimation until improvements in DAP point cloud generation can mitigate the canopy envelope effect and capture smaller trees and patches for better canopy cover mapping.

Our estimation framework was designed to mirror key aspects of current Forest Inventory and Analysis (FIA) methods, including the use of a single stratification layer derived from a canopy product. However, the precision of DAP-based estimates could likely be further improved by incorporating additional data for stratification or alternative estimation frameworks. Multiple plot-level metrics derived directly from the DAP point clouds or orthoimages could be combined in a model to create a layer for endogenous post-stratification, which often yields higher precision than traditional post-stratification (Mauro et al., 2022). For example, Pulkkinen et al. (2018) demonstrated improved precision using endogenous post-stratification based on multiple photogrammetric predictors. Additionally, incorporating

data from other sources like Landsat and Sentinel-2 has been shown to improve model performance (Frank et al., 2025; Strunk et al., 2022). This auxiliary data is highly compatible with alternative model-assisted estimators, which remain design-unbiased while typically yielding higher precision and are less limited by few plots within estimation units (Myllymäki et al., 2017; Pulkkinen et al., 2018).

5.3 Influence of Forest Type and Canopy Architecture

The diverse canopy architectures and tree spatial patterns across Rocky Mountain forest types heavily influenced DAP height accuracy and, ultimately, the estimation of forest area and AGB. DAP exhibited the lowest accuracy in pinyon-juniper woodlands, yielding negative R^2 values across all spatial scales for both *mean* height and *c2* cover, along with severe underestimation of cover. This was expected in sparse, short-stature canopies, as the semi-global matching algorithm implemented in Leica XPro likely filtered isolated trees as noise. Previous research has noted DAP's tendency to omit individual trees in low-density areas which could be due to resolution constraints, sensor types (i.e, frame or pushbroom), or image matching software configurations (Strunk et al., 2020). One study using 0.3 m and 0.7 m stereo satellite imagery similarly found that cost-based image matching often omits or underestimates trees smaller than 8 pixels in diameter (Loghin et al., 2020). While the original semi-global matching formulation (Hirschmuller, 2008) included parameters to penalize large depth changes and filter disparity peaks, commercial software rarely exposes these settings, limiting the ability to test parameter tunings that would be universal across implementations.

In spruce-fir forests, narrow terminal leaders often result in height underestimation of individual trees with DAP (Mielcarek et al., 2020), but the canopy-envelope of DAP CHMs lead to overestimated mean height and cover in our study. The point clouds essentially draped over the upper canopy, missing small gaps and the deep valleys between conical crowns. Despite near-zero explained variance across scales for these metrics, DAP paradoxically outperformed ALS slightly in post-stratified estimation efficiency for this forest type. DAP achieved its highest accuracy and, in some cases, achieved higher REs than ALS in aspen and ponderosa pine stands, which are characterized by broad, rounded crown shapes. Much of the previous research also indicates that DAP performs optimally in closed-canopy, deciduous stands (Michez et al., 2020; Mielcarek et al., 2020), including with NAIP imagery in the southeastern US (Prior et al., 2022). Ultimately, because *RE* gains remained relatively modest across all forest types, the primary

benefit of stratification likely stems from efficiently separating forest from non-forest rather than precisely modeling continuous variability within homogeneous stands.

5.4 Post-Fire Canopy Height and Change

Post-fire environments present another challenging forest context for DAP that bears similarity to the challenge with sparse forests. At standard statewide acquisition resolutions (e.g., 0.4-1 m), residual standing dead stems are typically too fine to reliably identify conjugate pixels during image matching, and isolated live crowns or patches must be sufficiently large to avoid being filtered out. As ALS-observed crown cover decreased with higher burn severity, DAP point clouds captured progressively fewer stems, resulting in near-total omission in high-severity areas and negative R^2 values for height measurement. Frank et al. (2025) similarly demonstrated that tree omission by DAP increases dramatically when post-fire canopy cover drops below 40-60%.

While counterintuitive, standard DAP CHMs might serve as a better proxy for *live* canopy height in burned landscapes compared to unfiltered ALS, precisely because DAP selectively registers large, intact foliage while missing defoliated snags. However, this is still speculative and requires thorough validation. What is explicitly clear is that ~0.6 m DAP alone cannot reliably measure residual snag heights in severe burns, severely limiting its utility for mapping post-fire wildlife habitat (Vogeler et al., 2016) or dead AGB for salvage logging (Frank et al., 2025). Considering that ultra-high-resolution (4.4 cm) UAV DAP can successfully classify burned individual trees and model scorch height (Arkin et al., 2023), future research should identify the exact resolution thresholds at which aerial DAP can adequately resolve dead stems.

Direct, repeat 3D measurement of canopy structure offers a significant potential advantage over spectral indices used in burn severity classification (e.g., dNBR) because of its ability to assess actual physical loss following wildfires. Because DAP systematically omitted residual dead trees, the bi-temporal DAP analysis indicated a much greater magnitude of structural loss in moderate and high-severity burn areas compared to bi-temporal ALS. Again, this greater loss may inadvertently map *live* canopy volume reduction more accurately than unfiltered ALS, though this requires further testing. However, when modeling relative changes in basal area, Frank et al. (2025) found that use of post-fire only DAP explained 19% less variance than ALS. To improve prediction of changes in basal area and leaf area index with bi-temporal lidar, Hu et al. (2019) developed profile area metrics that take the difference in

normalized vertical profiles of the pre-fire and post-fire point clouds. These metrics may be less effective with DAP point clouds, which do not capture the internal structure of canopies. Nonetheless, the distinct shifts in DAP-derived height distributions across burn severity classes suggest that further evaluation of multi-temporal DAP as a tool for structural burn severity characterization is highly warranted.

5.5 Potential for Technological and Operational Improvements

This study is a step towards filling critical research gaps in the operational use of DAP across broad extents, and there are many avenues for further developing use of this technology in forest monitoring. The imagery used in this study (i.e., 0.6 m pushbroom with low sidelap) was intended for generating orthomosaics rather than point clouds. Some research has indicated that DAP quality improves with higher sidelap (40-60%), higher resolution, and frame-based sensors (Goodbody et al., 2021; Strunk et al., 2020), but more testing is needed. Adjusting flight parameters for future NAIP acquisitions to enhance 3D mapping may be worthwhile to support forest monitoring and other applications, provided the benefits outweigh higher acquisition costs.

Furthermore, alternative image matching algorithms or configurations specifically tuned for forestry applications may substantially improve height retrieval (Strunk et al., 2020). Most photogrammetry software is currently based on semi-global matching (Hirschmuller, 2008). More recently there has been rapid development of alternative algorithms, such as variants of MVSNet and Neural Radiance Fields (Luo et al., 2024). Traditional algorithms like semi-global matching are still outperforming them in some aerial benchmarks (Nex et al., 2023), but testing these newer algorithms in aerial forest applications has only just begun.

6 Conclusion

This study demonstrates that multi-temporal DAP derived from operational aerial imagery can provide a viable, scalable alternative to ALS for certain broad-scale forest applications. Although DAP point clouds can miss fine interior canopy details, spatially aggregating these measurements to plot or landscape levels increases correspondence with ALS, making it a highly effective tool for supporting national forest inventories. Specifically, when used for the post-stratified estimation of AGB, DAP height strata yielded precision gains virtually identical to ALS. Furthermore, we confirmed that DAP achieves its highest accuracies in closed-canopy stands or those with broad, rounded crowns, such as aspen and

ponderosa pine dominated forests. Multi-temporal DAP was also able to characterize changes from wildfire that corresponded with spectral-based measures of burn severity.

At the same time, this study identified important limitations to consider in the use of similar DAP datasets, though there are still opportunities for improvement. DAP-derived heights exhibited systematic underestimation and greater uncertainty in structurally complex or sparse forests, with particularly poor performance in pinyon–juniper woodlands where low canopy cover and limited height variability reduce both accuracy and predictive power. DAP canopy cover metrics were unable to reflect moderate values at higher resolutions, but achieved similar accuracy statistics to Landsat-based predictive models at lower resolutions like 90 m. Despite this improvement, ALS-based cover strata were still far better in estimation of forest area. In post-fire environments, DAP failed to capture residual standing dead trees, resulting in higher apparent canopy losses than from ALS, but further validation is needed on how this corresponds with losses in height of live canopy specifically. Targeted collection parameters, improvements in image matching, incorporation of additional remote sensing data, and consideration of alternative estimation strategies may further mitigate some of these limitations. DAP's wall-to-wall coverage, lower cost, and increasing temporal availability make it a compelling complement to ALS, particularly for repeated, large-area monitoring and estimation. By accounting for these known limitations, DAP from national aerial imagery programs could be used to continuously track dynamic forest landscapes.

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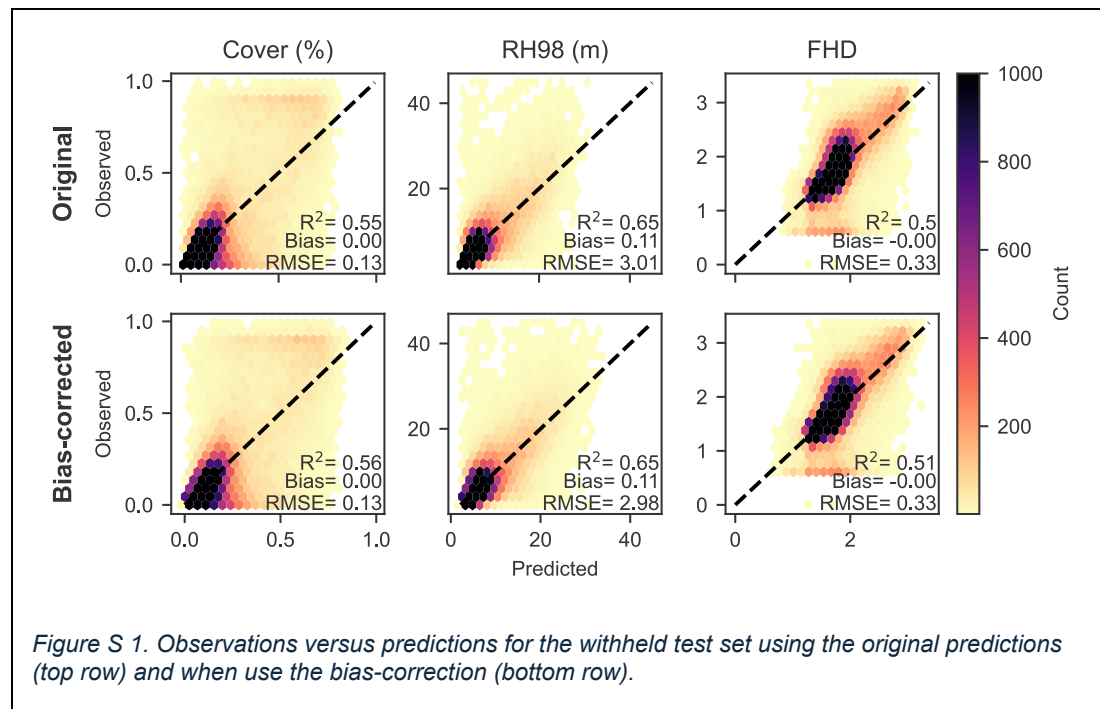
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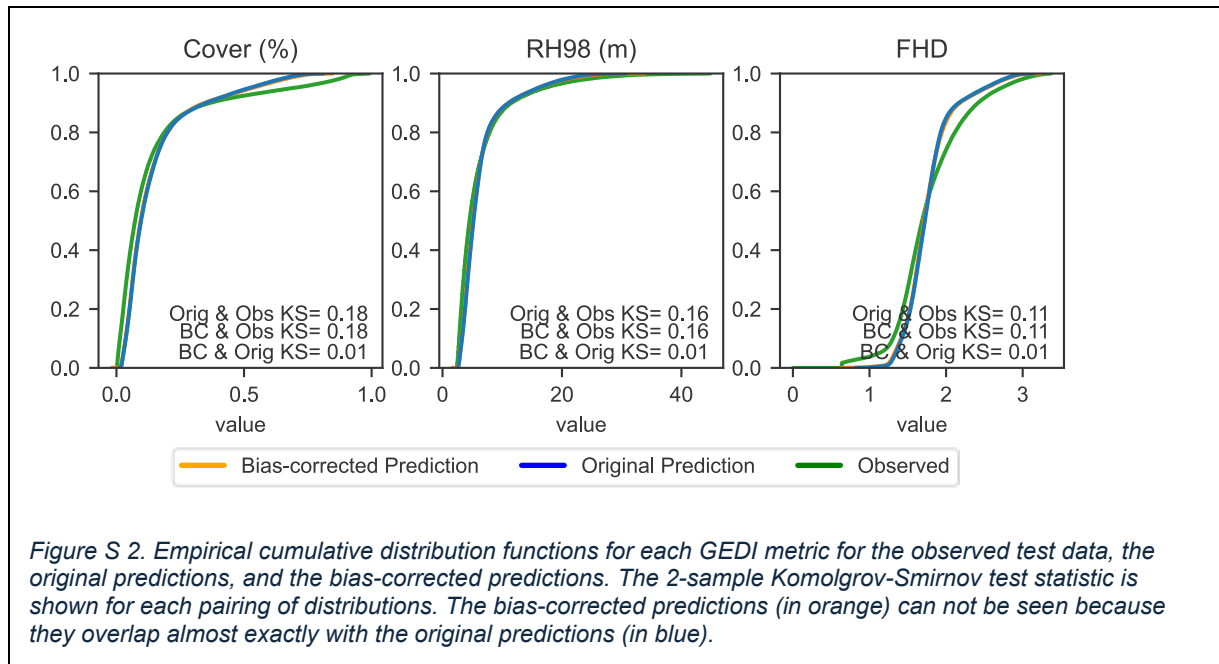
APPENDIX

1 Chapter 1 Appendix

1.1 Bias correction

Predictions of Cover and FHD tended to overestimate low values and underestimate high values, which is a common result in random forest and other machine learning models. We attempted to correct for this “regression to the mean” using the first random forest bias-correction method in Zhang and Lu (2012), BC1. The data was split into 70% for training and developing the bias correction and 30% for testing. We obtained residuals of the first random model, which served as the response variable in a second random forest model that included the out-bag predictions from the first random forest model along with the original covariates. These models were then applied in succession to the test data, and the final prediction was the sum of the GEDI metric predictions and the predictions of residuals. The bias-correction method only increased R^2 by 0.01 for Cover and FHD, and decreased RMSE by 0.03 for RH98. There was also no substantial change in the distribution of predictions, with a compression to the mean still present for Cover and FHD. Because the bias-correction added complexity with little improvement, we did not use it for the rest of the analysis and used the original random forest predictions instead.





1.2 Model comparison significance tests

We conducted paired Wilcoxon signed-rank tests comparing the absolute residuals of the model with the lowest RMSE for each metric against absolute residuals of the chosen model for the metric (Rainio et al., 2024). In this test, the null hypothesis is that the median of the differences between paired absolute residuals is zero.

Table S 1. Wilcoxon signed-rank test results (test statistic and p-value) comparing the model with the lowest RMSE against the chosen model for each GEDI metric.

Metric	Best model	Chosen model	Test statistic	p-value
Cover	CCDC ^{L30} + PALSAR + Soils + Topo	LandTrendr + PALSAR + Soils + Topo	19078281816.0	0.0087
RH98	CCDC ^{HLS} + PALSAR + Soils + Topo	LandTrendr + PALSAR + Soils + Topo	19091992411.0	0.0216
FHD	CCDC ^{L30} + PALSAR + Soils + Topo	LandTrendr + PALSAR + Soils + Topo	19078281816.0	0.0087
Normal				

2 Chapter 2 Appendix

2.1 LANDFIRE reclassification

Table S 2. Reclassification of circa 2016 LANDFIRE 2.0 Existing Vegetation Type Group Names.

Reclassification	Existing Vegetation Type Group Name (EVT_GP_N)
Agricultural	Agricultural-Close Grown Crop, Agricultural-Fallow/Idle Cropland, Agricultural-Orchard, Agricultural-Pasture and Hayland, Agricultural-Row Crop, Agricultural-Row Crop-Close Grown Crop, Agricultural-Vineyard, Agricultural-Wheat
Water	Open Water, Snow-Ice
Developed	Developed-High Intensity, Developed-Low Intensity, Developed-Medium Intensity, Developed-Roads, Developed-Upland Deciduous Forest, Developed-Upland Evergreen Forest, Developed-Upland Herbaceous, Developed-Upland Mixed Forest, Developed-Upland Shrubland, Developed-Wetland Herbaceous, Developed-Wetland Mixed Forest, Developed-Wetland Shrubland, Quarries-Strip Mines-Gravel Pits-Well and Wind Pads
Wetland-riparian	Depressional Wetland, Freshwater Marsh, Introduced Herbaceous Wetland Vegetation, Introduced Riparian Vegetation, Introduced Woody Wetland Vegetation, Western Herbaceous Wetland, Western Riparian Woodland and Shrubland
Grassland	Grassland, Introduced Annual Grassland, Introduced Annual and Biennial Forbland, Introduced Perennial Grassland and Forbland, Mixed grass Prairie, Sand Prairie, Shortgrass Prairie, Tallgrass Prairie
Shrubland	Big Sagebrush Shrubland and Steppe, Blackbrush Shrubland, Deciduous Shrubland, Desert Scrub, Greasewood Shrubland, Introduced Upland Vegetation-Shrub, Low Sagebrush Shrubland and Steppe, Mesquite Woodland and Scrub, Mountain Mahogany Woodland and Shrubland, Pinyon-Juniper Shrubland, Salt Desert Scrub, Sand Shrubland
Bare	Sparse Vegetation
Alpine tundra	Alpine Dwarf-Shrubland, Fell-field and Meadow, Dry Tundra
Aspen	Aspen Forest, Woodland, and Parkland, Aspen-Mixed Conifer Forest and Woodland
Mixed conifer	Douglas-fir-Ponderosa Pine-Lodgepole Pine Forest and Woodland, Douglas-fir-Grand Fir-White Fir Forest and Woodland
Pinyon-juniper	Juniper Woodland and Savanna, Pinyon-Juniper Woodland
Limber pine	Limber Pine Woodland
Lodgepole pine	Lodgepole Pine Forest and Woodland
Ponderosa pine	Ponderosa Pine Forest, Woodland and Savanna
Spruce-fir	Spruce-Fir Forest and Woodland
Transitional	Transitional Forest Vegetation, Transitional Herbaceous Vegetation, Transitional Shrub Vegetation

3 Chapter 3 Appendix

3.1 LANDFIRE Reclassification

Table S 3. Reclassification of circa 2016 LANDFIRE 2.0 Existing Vegetation Type Group Names.

Reclassification	Existing Vegetation Type Group Name (EVT_GP_N)
Agricultural	Agricultural-Close Grown Crop, Agricultural-Fallow/Idle Cropland, Agricultural-Orchard, Agricultural-Pasture and Hayland, Agricultural-Row Crop, Agricultural-Row Crop-Close Grown Crop, Agricultural-Vineyard, Agricultural-Wheat
Water	Open Water, Snow-Ice
Developed	Developed-High Intensity, Developed-Low Intensity, Developed-Medium Intensity, Developed-Roads, Developed-Upland Deciduous Forest, Developed-Upland Evergreen Forest, Developed-Upland Herbaceous, Developed-Upland Mixed Forest, Developed-Upland Shrubland, Developed-Wetland Herbaceous, Developed-Wetland Mixed Forest, Developed-Wetland Shrubland, Quarries-Strip Mines-Gravel Pits-Well and Wind Pads
Wetland-riparian	Depressional Wetland, Freshwater Marsh, Introduced Herbaceous Wetland Vegetation, Introduced Riparian Vegetation, Introduced Woody Wetland Vegetation, Western Herbaceous Wetland, Western Riparian Woodland and Shrubland
Grassland	Grassland, Introduced Annual Grassland, Introduced Annual and Biennial Forbland, Introduced Perennial Grassland and Forbland, Mixed grass Prairie, Sand Prairie, Shortgrass Prairie, Tallgrass Prairie
Shrubland	Big Sagebrush Shrubland and Steppe, Blackbrush Shrubland, Deciduous Shrubland, Desert Scrub, Greasewood Shrubland, Introduced Upland Vegetation-Shrub, Low Sagebrush Shrubland and Steppe, Mesquite Woodland and Scrub, Mountain Mahogany Woodland and Shrubland, Pinyon-Juniper Shrubland, Salt Desert Scrub, Sand Shrubland

Bare	Sparse Vegetation
Alpine tundra	Alpine Dwarf-Shrubland, Fell-field and Meadow, Dry Tundra
Aspen	Aspen Forest, Woodland, and Parkland, Aspen-Mixed Conifer Forest and Woodland
Mixed conifer	Douglas-fir-Ponderosa Pine-Lodgepole Pine Forest and Woodland, Douglas-fir-Grand Fir-White Fir Forest and Woodland
Pinyon-juniper	Juniper Woodland and Savanna, Pinyon-Juniper Woodland
Limber pine	Limber Pine Woodland
Lodgepole pine	Lodgepole Pine Forest and Woodland
Ponderosa pine	Ponderosa Pine Forest, Woodland and Savanna
Spruce-fir	Spruce-Fir Forest and Woodland
Transitional	Transitional Forest Vegetation, Transitional Herbaceous Vegetation, Transitional Shrub Vegetation