UNIVERSIDAD POLITÉCNICA DE MADRID

ESCUELA TÉCNICA SUPERIOR DE INGENIERÍA DE MONTES, FORESTAL Y
DEL MEDIO NATURAL

APLICACIONES DE LA FOTOGRAMETRÍA DIGITAL
AÉREA EN EL INVENTARIO FORESTAL

TESIS DOCTORAL

José Antonio Navarro Fernández
Ingeniero de Montes

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A Emilio

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Resumen

La gestión forestal sostenible y los mecanismos de monitoreo, reporte y verificación de gases de efecto invernadero en proyectos forestales de mitigación del Cambio Climático necesitan de información actual y precisa de los recursos forestales y los stocks de carbono. En este sentido, la información tridimensional (3D) de alta resolución proveniente de sensores aerotransportados ha mostrado ser una fuente útil para caracterizar e inventariar y caracterizar los recursos forestales, permitiendo una mejora en la toma de decisiones. En las últimas décadas, el uso del escáner láser aerotransportado (ALS) se ha usado ampliamente para la caracterización de la estructura de la vegetación en masas forestales y la estimación de variables dasométricas de forma continua. Sin embargo, los recientes avances en capacidad de computación y mejoras en los algoritmos fotogramétricos han motivado un creciente interés en la fotogrametría digital aérea (DAP) como una alternativa económica al ALS. Esta atención a la DAP viene acompañada por dos grandes hechos: la adquisición frecuente y regular de imágenes aéreas por parte de agencias nacionales en multitud de países, y el creciente mercado de los vehículos aéreos no tripulados (UAVs), que hace que estos sean cada vez más asequibles y su utilización más común.

Esta tesis, que forma parte de un proyecto de investigación industrial, tiene como objetivo analizar el uso de la DAP en el inventario forestal a partir de imágenes aéreas adquiridas desde diferentes plataformas y mediante diferentes aproximaciones. Los Capítulos 2 y 3 utilizan métodos de masa (ABA) y nubes de puntos DAP generadas a partir de imágenes tomadas en vuelos tripulados por agencias nacionales, mientras que el Capítulo 4 utiliza métodos de árbol individual (ITC) e imágenes tomadas desde UAV.

En el Capítulo 2 se compararon las nubes de puntos ALS y DAP, y se analizó el desempeño de ambas tecnologías en la modelización de distintas variables forestales en una masa de *Pinus pinaster* Ait. del Sistema Central (España). Los resultados de este estudio mostraron que los datos DAP ofrecen precisiones comparables a los datos ALS en la estimación de variables de inventario.

En el Capítulo 3 se plantea un nuevo método para la construcción de modelos de volumen maderable (V) que sean transferibles temporalmente y entre nubes de puntos 3D generadas con ambas metodologías (ALS y DAP). Para ello se han seleccionado variables estables entre las diferentes fuentes de datos DAP y ALS. En este estudio se utilizaron diferentes datos ALS y DAP e información de campo de distintos años de una masa de *Pinus sylvestris* L. Los resultados de esta investigación sugieren que no sólo es posible generar modelos de V transferibles en el tiempo, sino que también se pueden construir modelos a

partir de datos ALS que sean transferibles a nubes de puntos DAP sin una pérdida significativa de precisión.

Finalmente, en el Capítulo 4 se plantea una nueva metodología para el inventario de la biomasa aérea (AGB) en plantaciones jóvenes de manglar. En este estudio, los árboles inventariados fueron medidos mediante ITC a partir de nubes de puntos DAP generadas con imágenes de UAV. Los valores de AGB de cada parcela se utilizaron para ajustar modelos de predicción usando datos satelitales radar y multiespectrales como información auxiliar. Los resultados revelaron que las imágenes UAV pueden ser utilizadas mediante DAP para la correcta detección y delineación de las copas de los árboles en la zona de estudio, aunque este método subestimó ligeramente las mediciones de la altura de los pies y el diámetro de copa. La utilización de datos satelitales permitió una mejora significativa de los estimadores poblacionales de AGB.

Esta tesis demuestra el gran potencial de la DAP en el campo de los inventarios forestales y el monitoreo de la vegetación. Los resultados revelan que, independientemente de la plataforma utilizada para la adquisición de las imágenes aéreas, la DAP es una tecnología que debe ser tomada en cuenta en los próximos años por los gestores forestales.

Abstract

Sustainable forest management and monitoring, reporting and verification (MRV) systems of forest-based approaches to climate change mitigation require up-to-date and accurate information on forest resources and carbon stocks. In this regard, three-dimensional (3D) remote sensing data have been proven to be a useful source of information to characterize and inventory forest resources, allowing for enhanced decision making. In the last few decades, airborne laser scanning (ALS) has been widely used to characterize forest structure and for wall-to-wall mapping forest attributes. However, recent advances in computational capacity and photogrammetric algorithms have led to a growing interest in digital aerial photogrammetry (DAP) as a cost-effective alternative to ALS. This emphasis on DAP is matched by two major developments: the regular and frequent acquisition of aerial imagery by national agencies in many countries, and the growing market for unmanned aerial vehicles (UAVs), which makes them increasingly affordable and commonly used.

This thesis, which is part of an industrial research project, aims to analyze the use of DAP data in forest monitoring using aerial imagery acquired using different platforms and by using different approaches. An area-based approach (ABA) and DAP point clouds derived from national mapping campaigns imagery were used in Chapters 2 and 3. On the other hand, individual tree crown approach (ITC) and UAV-derived imagery were used in Chapter 4.

ALS and DAP point clouds were compared in Chapter 2. In this study, performance of different forest attributes ABA models fitted using ALS and DAP-derived data was compared. This research was conducted on a *Pinus pinaster* Ait. forest of Central Iberia. The results of this study revealed that predictions accuracy of DAP-based models was comparable to accuracy of ALS-based forest attributes models.

Chapter 3 discusses a new method for building growing stock volume (V) which may be transferred not only to point clouds acquired using the same technology (ALS-ALS and DAP-DAP transferability) but also between both technologies (ALS-DAP transferability). For this purpose, stable metrics were selected among the different DAP and ALS data sources used. Field surveys from different years and different DAP and ALS datasets were used. This study was conducted on a *Pinus sylvestris* L. stand in Central Iberia. The results suggest not only the potential to generate temporal transferable V models, but also to build models from ALS data which can be applied with DAP point clouds without significant accuracy loss.

Finally, Chapter 4 proposes a new methodology for above-ground biomass (AGB) in young mangrove plantations monitoring. In this study, surveyed trees were measured with an ITC

approach using UAV imagery-derived point clouds. AGB values of each plot were used to fit prediction models using radar and multispectral satellite data as auxiliary information. The results revealed that UAV imagery may be used with DAP for proper detection and delineation of tree crowns in the study area, although this method slightly underestimated tree heights and crown diameters. Multispectral and radar data enabled a significant enhancement of AGB population estimators.

This thesis demonstrates the great potential of DAP in forest inventories and canopy monitoring. The results reveal that, regardless of the platform used to collect aerial images, DAP is a technology that must be considered in future by forest managers.

Capítulo 1. Introducción

1.1 Antecedentes: Inventario forestal y sensores remotos

Los bosques y otras formaciones arboladas cubren el 30.6% de la superficie terrestre y prestan importantes servicios ecosistémicos (FAO, 2015). Su correcta gestión contribuye al logro de los Objetivos de Desarrollo Sostenible de la Agenda 2030 para el Desarrollo Sostenible relacionados con los medios de vida y la seguridad alimentaria (FAO, 2018). Gracias a la capacidad para almacenar carbono en su biomasa a medida que crecen, uno de los papeles más importantes de los bosques es su participación en el ciclo global del carbono, jugando un doble rol como fuentes y sumideros de carbono (Pan et al., 2011).

Dadas las crecientes necesidades de gestión forestal sostenible, es preciso contar con información detallada y precisa de las características estructurales de las masas. Los inventarios forestales permiten a los gestores contar con datos prácticos para la toma de decisiones y la apropiada ordenación de los recursos atendiendo a diferentes criterios y objetivos (Fekety et al., 2015). Los inventarios forestales se pueden llevar a cabo a muchas escalas y con diferentes propósitos (Kangas et al., 2018a). Sin embargo, se realizan principalmente a dos escalas: los Inventarios Forestales Nacionales (IFN), con el objeto de generar estadísticas regionales y nacionales, y los inventarios a una mayor escala para la planificación a nivel de monte o de conjunto de montes.

Los IFN se llevan a cabo para obtener estadísticas forestales a nivel nacional o internacional y son la mayor fuente de información forestal debido al gran número de parcelas y de variables medidas, por lo que son cruciales para establecer políticas forestales (Alberdi, 2015; Fridman et al., 2014; Tomppo et al., 2010). Los IFN tal y como hoy se conocen, nacieron a principios del siglo XX en los países nórdicos (Tomppo et al., 2010). Normalmente consisten en una red de parcelas permanentes, basada en un muestreo probabilístico, que se miden continuamente en ciclos de 5-10 años. Los inventarios basados únicamente en parcelas de campo implican un gran gasto de recursos que puede reducirse utilizando información auxiliar, como cartografía básica o mapas generados a partir de imágenes satelitales o fotointerpretación de imágenes aéreas (Tomppo et al., 2008). Así, los datos de sensores remotos no sólo han contribuido a un aumento en la eficiencia y la precisión de los IFN al usarse como fuente de información básica para el diseño del inventario, sino que también han posibilitado la generación de cartografía de variables forestales con resoluciones espaciales que de otra forma serían imposibles (McRoberts and Tomppo, 2007) gracias a su uso como variables auxiliares en modelos de predicción (Rahlf et al., 2017; Tomppo, 1990).

En superficies menores, la precisión de los IFN no suele ser suficiente y es necesaria una mayor resolución espacial de las estimaciones para poder hacer una correcta

planificación de la gestión forestal. Para ello, se realizan los inventarios a escala de monte o de montes agrupados. Tradicionalmente, estos inventarios se han realizado a través la medición de parcelas de campo basadas en muestreos probabilísticos apoyados en fotografías aéreas o cartografía temática (Næsset, 2014). Sin embargo, en las últimas décadas se ha generalizado el uso de datos tridimensionales (3D) de sensores remotos para la caracterización de la estructura de la vegetación de forma espacialmente continua (Hall et al., 2005; Holmgren et al., 2003; Maltamo et al., 2005; Næsset, 2002a). El uso de esta información permite obtener inventarios más detallados, más precisos y espacialmente explícitos que los inventarios tradicionales (White et al., 2013a).

Además de la incorporación de datos 3D en la generación de información forestal, desde hace décadas existe un incremento exponencial en la disponibilidad de datos satelitales de diversos tipos y resoluciones que pueden utilizarse para mejorar el conocimiento de los bosques, con la ventaja de que estos sensores pueden cubrir grandes superficies y visitar cada zona en cortos periodos de tiempo. Por ejemplo, el programa Copernicus de la Comisión Europea ofrece acceso gratuito y abierto a datos radar y multiespectrales generados por las misiones Sentinel-1 y Sentinel-2. Gracias a ello, es posible inventariar zonas remotas o de difícil acceso, no solo en países desarrollados, sino en cualquier rincón del planeta. En los próximos años, los datos 3D de misiones satelitales como la Global Ecosystem Dynamics Investigation (GEDI) o la Ice, Cloud, and Land Elevation Satellite 2 (ICESAT-2) podrán ser utilizadas como información auxiliar en inventarios forestales a diferentes escalas y con distintos propósitos.

1.2 Airborne Laser Scanning

El LiDAR (Light Detection and Ranging) es un sistema activo de detección remota basado en un sensor laser. En la tecnología LiDAR aerotransportada (ALS, por sus siglas en inglés, Airborne Laser Scanning) el instrumental se monta en un avión y el sistema LiDAR mide el tiempo de ida y vuelta de un pulso láser. El sensor emite miles de pulsos laser por segundo que inciden sobre la superficie sobrevolada, rebotan y se reflejan sobre el sensor (Baltsavias, 1999a; Dubayah and Drake, 2000). Sabiendo la posición y la orientación del sensor de manera precisa gracias a la integración de un equipo GPS y una unidad de medición inercial, es posible definir las coordenadas (x, y, z) del objeto medido (White et al., 2013a).

Una de las principales características, y que supone una ventaja del ALS frente a otras tecnologías, es la capacidad de registrar múltiples retornos por cada pulso emitido cuando éste intercepta una superficie que puede penetrar, como es el caso de las ramas y las hojas de la vegetación. De esta forma, el ALS puede caracterizar de manera precisa la estructura

3D de la vegetación (Vauhkonen et al., 2014). La capacidad del ALS de penetrar dentro en la vegetación permite generar modelos digitales del terreno (DTM, por sus siglas en inglés, digital terrain model) incluso en áreas pobladas con vegetación densa. El DTM permite normalizar las alturas de los puntos y asignar a cada uno una coordenada z relativa al nivel de suelo.

Figure 1.1 Capacidad multirretorno del ALS y comportamiento de los pulsos dependiendo del tipo de superficie en la que inciden.

Aunque los primeros experimentos con ALS en el sector forestal datan de los años 70 (Vauhkonen et al., 2014), no ha sido hasta las dos últimas décadas cuando su uso se ha extendido hasta el punto de que hoy en día es utilizado de forma operativa en inventarios forestales de multitud de países (Næsset, 2007). Aunque actualmente el ALS se usa de forma generalizada en la estimación de variables de inventario como la altura dominante, el área basimétrica o el volumen (Fernández-Landa et al., 2018; Holmgren et al., 2003; Lefsky et al., 1999; Næsset, 2002a), tiene además muchas otras aplicaciones en el ámbito forestal, como el análisis de la complejidad estructural de la vegetación (Kane et al., 2010), la caracterización del combustible forestal (González-Ferreiro et al., 2014; Marino et al., 2018), la modelización de hábitats (Hinsley et al., 2002), el estudio de la madera muerta (Kim et al., 2009) o la cuantificación de los daños por viento (Chirici et al., 2018).

1.3 Fotografía aérea y fotogrametría

La Sociedad Estadounidense de Fotogrametría y Teledetección (ASPRS, 2019) define la fotogrametría como el "arte, ciencia y tecnología para la obtención de mediciones fiables de objetos físicos y el medio ambiente, a través de grabación, medida e interpretación de imágenes y patrones de energía electromagnética radiante y otros fenómenos". El principio de la fotogrametría clásica con imágenes estereoscópicas es semejante a la visión estereoscópica de los humanos (Iglhaut et al., 2019). A partir de imágenes de un objeto tomadas desde diferentes posiciones, se utiliza la percepción de profundidad de éste en las imágenes para asignarle unas coordenadas relativas. Generando rayos que pasen por el objeto y por el centro de proyección de la imagen, es posible resolver por triangulación la posición del objeto. Para ello, es necesario conocer los parámetros de orientación interna y externa de la cámara. Mediante el uso de puntos de apoyo en terreno, es posible, además, asignar coordenadas geodésicas al objeto (Pozuelo, 2003).

Los inicios de la fotogrametría se remontan a 1862, cuando el ingeniero militar francés Aimé Laussedat consiguió obtener planos exactos de edificios a partir de imágenes tomadas desde tejados de París (Jiang et al., 2008). Cuatro años antes, en 1858 se tomó la primera fotografía aérea desde un globo aerostático (Linares and García, 1996). No fue, sin embargo, hasta principios del siglo XX cuando se empezaron a utilizar imágenes aéreas en el ámbito forestal. En 1919 se realizaron los primeros ensayos para aplicar la fotografía aérea al estudio de las masas forestales (Carderera, 1956). En España, de Cañedo-Argüelles (1928) reporta las posibilidades de utilizar las técnicas fotogramétricas a partir de fotografías aéreas para el estudio de los bosques. En los siguientes años la fotogrametría aérea se hizo común en muchos países desarrollados y se utilizó profusamente en el ámbito forestal, pues permitía adquirir información auxiliar de manera masiva, reduciendo tiempo y costes para cartografiar grandes áreas. La información de imágenes aéreas se ha venido usando desde entonces con diferentes propósitos en los inventarios forestales, como el conteo de árboles, la estratificación o la medida de alturas de árboles (Carderera, 1959).

Aparte de la importancia que tuvo el uso de pares estereoscópicos en la planificación de las operaciones forestales y en el diseño de los inventarios, también permitía estimar volúmenes maderables a partir de tablas de producción y perfiles verticales de los rodales (Hugershoff, 1933). A finales del siglo XX en los países nórdicos, la fotogrametría aérea era el método básico para el apeo de rodales y las mediciones de fracción de cuba cubierta. La altura media de los rodales estimada por fotogrametría era utilizada para calibrar modelos de predicción de volumen de madera, reduciendo considerablemente los trabajos de campo (Næsset, 2014).

1.4 Fotogrametría Digital Aérea

En la década de los 80 se desarrollaron los primeros algoritmos de correlación automática (dense image matching), dando comienzo a la fotogrametría digital (Ackermann, 1984; Gruen, 1985). En la década de los 90 se consolidaron los métodos de correlación automática de imágenes con la aparición de multitud de softwares fotogramétricos para generar modelos digitales de superficie (DSM) y DTMs (Remondino et al., 2014). Se pasó de la fotogrametría por pares estereoscópicos al enfoque *multi-view*, el cual analiza la correspondencia de píxeles en múltiples imágenes. Sin embargo, pese a los avances en el proceso fotogramétrico, la aparición del ALS hizo que fueran pocos los ensayos que se realizaran usando nubes de puntos generadas por fotogrametría digital aérea (DAP) en los inventarios forestales (Næsset, 2002b).

En la última década, los avances en poder de computación y la mejora de algoritmos de visión por computador y de los métodos fotogramétricos, han dado lugar a un creciente interés por el uso de imágenes para la generación de modelos 3D. Los modelos 3D generados a partir de imágenes resultan en características geométricas similares a los generados mediante ALS, pero con costes menores (Remondino et al., 2014). De entre todos los métodos fotogramétricos desarrollados en los últimos años, el que más éxito y aceptación ha tenido es el Structure from Motion (SfM). Aunque el SfM es sólo una parte del proceso fotogramétrico completo, se suele denominar a todo el flujo de trabajo simplemente como SfM. La principal ventaja del SfM es su alto grado de automatización y la posibilidad de utilizar colecciones de imágenes no estructuradas y cámaras no calibradas.

El primer paso en el flujo de trabajo del SfM es la detección automática de *puntos clave* o *keypoints* mediante algoritmos como el Scale-invariant feature transform (SIFT) (Lowe, 1999). Este algoritmo encuentra puntos de características invariantes a factores de escala, traslación, rotación y parcialmente invariantes a cambios de iluminación y afinidades en las diferentes imágenes. Estos puntos clave son después utilizados por el SfM para resolver todos los parámetros de orientación interna y externa y generar una nube de puntos dispersa. Posteriormente se perfeccionan los resultados del SfM mediante un ajuste de bloques (*bundle adjustment*). Los puntos de esta nube se denominan *puntos de enlace* o *tie points*. El último paso es la densificación de la nube de puntos mediante algoritmos *multi-view stereo* (MVS), los cuales utilizan las posiciones y parámetros de orientación de las cámaras obtenidas por el SfM (Furukawa and Hernández, 2015). La mayoría de los softwares fotogramétricos comerciales actuales se basan en este flujo de trabajo, si bien cada uno está particularizado con su propia propagación y algoritmos no publicados.

Todos estos desarrollos se han dado paralelamente a la expansión y el crecimiento del mercado de los vehículos aéreos no tripulados (UAV, por sus siglas en inglés), potenciando además este proceso. Los UAV pueden montar una amplia gama de sensores, aunque lo más frecuente es que vayan equipados con cámaras fotográficas estándar. Una de las mayores ventajas de los UAV aplicados a la gestión forestal es la posibilidad de generar datos 3D de muy alta resolución espacial y temporal de forma rápida y barata (Goodbody et al., 2017b). Sin embargo, el área que pueden cubrir en cada vuelo está limitada tanto tecnológicamente por la capacidad de las baterías como normativamente por la legislación vigente particular de cada país, que habitualmente es restrictiva. Esto provoca que los UAV no sean una alternativa para la adquisición de datos DAP a gran escala, pero que a escalas reducidas sean una buena fuente de datos remotos para la estimación de variables forestales (Giannetti et al., 2018; Lisein et al., 2013; Puliti et al., 2015).

La DAP a partir de imágenes generadas por vuelos tripulados tiene un gran potencial para la estimación de variables de inventario dado los bajos costes de adquisición de datos frente al ALS. Esto es debido a que los vuelos fotogramétricos se configuran a mayores altitudes y con mayores distancias entre pasadas. De esta forma, los vuelos ALS son muchas veces inasumibles cuando la superficie de estudio es pequeña (Baltsavias, 1999b; Leberl et al., 2010). Si bien muchos países han implementado campañas nacionales de adquisición de datos ALS, o siguen haciéndolo, principalmente con fines cartográficos (Fernández-Landa, 2015; Noordermeer et al., 2019), los datos capturados suelen quedar desactualizados perdiendo su utilidad para el estudio de las masas forestales, ya que hasta ahora las campañas nacionales han sido únicas o con periodos de actualización demasiado largos para monitorizar el crecimiento de la vegetación y los cambios por perturbaciones en las masas. Sin embargo, las campañas nacionales o regionales de adquisición de imágenes aéreas para la producción de ortofotos están más arraigadas y se realizan con mayor frecuencia. Esta es una de las principales ventajas de la fotogrametría, puesto que las nubes de puntos DAP pueden obtenerse como un subproducto de las ortofotos (Noordermeer et al., 2019; Straub et al., 2013).

Hay que significar que las nubes de puntos obtenidas por DAP tienen diferencias con las generadas mediante ALS (White et al., 2013b). Así, la calidad de la nube de puntos DAP depende de varios factores que no afectan de la misma forma al ALS. Las oclusiones pueden suponer una limitación importante en la correlación automática de imágenes. Este condicionante es parcialmente solucionable aumentando el solape longitudinal y transversal en la adquisición de imágenes (Haala et al., 2010). Otra limitación que se presenta es la sensibilidad de la DAP a las diferencias en la reflectancia de las superficies desde diferentes perspectivas y a las sombras de los árboles, pues dificultan el proceso

fotogramétrico (Cavegn et al., 2014; St-Onge et al., 2008). Finalmente, la gran diferencia de la DAP frente al ALS es la incapacidad de penetrar la vegetación y generar un DTM en zonas arboladas. Por este motivo es necesario utilizar un modelo digital generado a partir de datos ALS para normalizar la nube de puntos DAP y obtener las alturas de los puntos de vegetación (Baltasvias, 1999b). Esto no es un problema en los países que han realizado campañas nacionales de toma de datos ALS, pues se pueden generar DTM de alta resolución espacial a partir de los datos disponibles (Noordermeer et al., 2019).

Figure 1.2 Normalización de datos generados mediante DAP a partir de un DTM creado usando datos ALS.

La estimación de variables de inventario forestal usando datos DAP generados a partir de imagen obtenida por cámaras métricas montadas en aviones tripulados y normalizados con ALS ha sido evaluada en múltiples estudios en diferentes tipos de masas y con diferentes configuraciones de vuelo. Principalmente se ha probado su uso en los países nórdicos, centroeuropeos y en Canadá (Bohlin et al., 2017, 2012; Järnstedt et al., 2012; Nurminen et al., 2013; Rahlf et al., 2015; St-Onge et al., 2015; Stepper et al., 2014a; Vastaranta et al., 2013; White et al., 2013b). Los resultados de estos estudios han demostrado que, si bien las precisiones en la estimación de atributos forestales suelen ser menor que usando ALS, éstas son de un orden cercano de magnitud. Kangas et al. (2018b) realizaron un estudio comparativo entre DAP y ALS que analizaba la precisión de las estimaciones de diferentes variables forestales y evaluaba los costes/pérdidas en la utilización de cada fuente de datos en Noruega. Los resultados de este estudio muestran que las diferencias

en la precisión de las estimaciones entre ambas tecnologías son despreciables y que la decisión de usar DAP o ALS debe tomarse teniendo en cuenta la disponibilidad de datos y los costes de adquisición.

En los inventarios basados en el uso de UAV podría no ser tan importante contar con un DTM previo generado mediante ALS, ya que Giannetti et al. (2018) demostraron que es posible estimar el volumen maderable a partir de nubes de puntos DAP generadas a partir de imágenes de UAV, sin necesidad de normalizar la nube de puntos, utilizando variables de textura e intensidad de la imagen. La precisión de las estimaciones mediante este método fue comparable a la obtenida usando ALS y DAP normalizada con ALS. Sin embargo, esta metodología no se ha estudiado con datos DAP generados a partir de imágenes aéreas de aviones tripulados.

1.5 Método de masa y árbol individual

Tradicionalmente se han utilizado dos maneras de abordar la relación entre los datos 3D y los datos de campo: el método de masa (ABA, por sus siglas en inglés, area-based approach) y la detección de árboles individuales o método de árbol individual (ITC, por sus siglas en inglés, individual tree crown). En esta tesis se ha utilizado el ABA en los capítulos 2 y 3, y la ITC en el capítulo 4.

El método de masa fue utilizado por primera vez con ALS en Næsset (2002a) y con DAP en Næsset (2002b). En el ABA se utilizan todos los puntos que intersecan con los límites de las parcelas de campo para calcular diversos estadísticos de altura, dispersiones de altura y cobertura. Estos estadísticos son después utilizados como variables independientes para predecir las variables objetivo medidas en campo a través de modelos de predicción (Næsset, 2002a). Además de estadísticos relacionados con la distribución tridimensional de los puntos de los datos ALS o DAP, también pueden usarse variables espectrales (Kachamba et al., 2016; Popescu et al., 2004; Puliti et al., 2017) y la información de textura extraída de los modelos digitales de altura de vegetación (CHM, por sus siglas en inglés, canopy height model) (Haralick et al., 1973; Ozdemir and Donoghue, 2013). El objetivo del ABA es generar estimaciones espacialmente explícitas en continuo de las variables estudiadas (Næsset, 2002a). Para ello, en una segunda fase, es necesario dividir el área de estudio en celdas que contengan los mismos estadísticos usados en el modelo de predicción y aplicar éste a cada una de las celdas. El tamaño de las celdas debe ser lo más parecido posible al de las parcelas de campo (Magnussen and Boudewyn, 1998). Aunque en este método no es necesario conocer la posición exacta de los árboles dentro de las parcelas, sí que es necesario localizar con precisión los límites de las parcelas.

Normalmente se utilizan parcelas circulares por su simplicidad de delimitación en campo, ya que sólo se requiere establecer con precisión el punto central frente a las cuatro esquinas de las parcelas cuadradas (Adams et al., 2011; White et al., 2013a). El método de masa ha sido ampliamente utilizado y es el más común en la estimación de variables forestales tanto en ALS (Holmgren, 2004; Næsset, 2002a) como en DAP (Bohlin et al., 2012; Vastaranta et al., 2013).

Figure 1.3 Ejemplos de cartografía de inventarios generados usando a) métodos de masa y b) métodos de árbol individual

En el ITC se trata de identificar y delinear las copas de cada árbol sobre las nubes de puntos o modelos digitales. Una vez segmentados los árboles se pueden extraer o modelizar las variables de interés a nivel de árbol (Honkavaara et al., 2013). La información a nivel de árbol puede utilizarse para determinar variables de masa a nivel de parcela, de rodal o unidades mayores. La segmentación de los árboles puede realizarse usando algoritmos que trabajan directamente sobre las nubes de puntos, sobre CHM o una combinación de ambos (Kandare et al., 2017). Aunque existen diferentes métodos, cuando se trata de segmentar las copas de los árboles, normalmente se parte por la detección de los ápices

a partir del CHM y usando métodos de detección de máximos locales (Liu et al., 2015). Estos métodos asumen que los máximos locales representan los ápices de cada pie, lo cual es frecuente en las coníferas pero no tanto en las frondosas, por lo que puede resultar en una sobreestimación de la delimitación de las copas (Wang, 2010). Para mejorar la identificación de máximos locales se utilizan frecuentemente ventanas de búsqueda de tamaño variable, relacionando el tamaño variable de la ventana con el tamaño de las copas de una especie y la altura de cada punto (Kini and Popescu, 2004; Popescu et al., 2002). Una vez detectados los árboles, se procede a la delimitación de las copas. Para este proceso existen multitud de métodos, como el de "cuencas inundables" o *watershed* (Carleer et al., 2005), los de tipo *region growing* (Hyypä et al., 2001) o los *valley following* (Gougeon, 1995). Esta segmentación depende fundamentalmente de la detección de árboles, por lo que puede resultar en errores por omisión y por comisión de árboles, sobre todo en DAP, pues ésta es más sensible a las sombras y oclusiones. Así, es frecuente que las estimaciones realizadas por este método a nivel de rodal tengan errores sistemáticos (Hyypä and Inkinen, 1999).

1.6 Inventarios basados en modelos e inventarios basados en diseño

Como ya se ha mencionado, los datos de sensores remotos se pueden utilizar tanto en la fase de diseño de inventario como en la estimación de variables a través de modelos de predicción. Normalmente se han seguido dos grandes tipos de inferencia a la hora de utilizar estos modelos para mejorar los estimadores o las estimaciones de las variables (Ståhl et al., 2016); la inferencia basada en modelos (model-based) y la basada en el diseño de muestreo (design-based).

La inferencia basada en el diseño precisa que el muestreo sea probabilístico, por ejemplo, un muestreo aleatorio simple o uno sistemático. Los estimadores en este marco de inferencia, como el estimador de Horvitz-Thompson (Särndal et al., 1992), se basan únicamente en el diseño del muestreo probabilístico. Sin embargo, los modelos basados en sensores remotos pueden ser usados para mejorar los estimadores reduciendo las varianzas a través de las estimaciones "asistidas por modelo" (model-assisted). Este tipo de estimaciones pueden considerarse insesgadas independientemente de las características del modelo empleado (Ståhl et al., 2016).

En la inferencia basada en modelos se asume que existe un modelo que produce los valores aleatorios de la población (Särndal et al., 1978). En el caso típico se asume que se

dispone de información auxiliar para todos los elementos de la población. Además, como el muestreo sólo se utiliza para entrenar los modelos, no tiene que ser necesariamente un muestreo probabilístico (Ståhl et al., 2016). Es decir, se pueden usar muestreos dirigidos. Por tanto, el inventario suele ser más cómodo y se reducen los costes (McRoberts et al., 2015b). Como los estimadores en la inferencia basada en modelos dependen únicamente de los modelos, es más importante que en la inferencia basada en el diseño prestar atención a la calidad del modelo para que las estimaciones sean sesgadas (Næsset et al., 2011).

En esta tesis sólo se han utilizado estimadores poblacionales en el capítulo 4. En concreto, el método de inferencia usado fue el basado en el diseño y model-assisted.

1.7 Actualización de inventarios

Los montes gestionados de muchos países se inventarían tradicionalmente cada 10-20 años de forma recurrente (Nyström et al., 2015). Si bien estos plazos para la recolección de información del estado de las masas son suficientes para una correcta planificación de la gestión forestal, no se acercan realmente a los tiempos de la gestión debido a que la vegetación puede sufrir cambios entre los dos inventarios. De esta forma, los inventarios deben actualizarse para reflejar correctamente el estado actual de la masa. Existen dos tipos de cambios que deben detectarse y recogerse en una actualización de inventario: aquellos que causan pérdidas en el stock como las cortas, incendios o daños por viento o nieve, y aquellos que suponen acumulaciones, como los debidos al crecimiento o a la regeneración natural. En masas productivas, el uso de información poco precisa y desactualizada aumenta la incertidumbre y el potencial error en las previsiones del volumen maderable, generando potenciales pérdidas económicas (Goodbody et al., 2017b). Por ello, es necesario contar con información lo más actualizada posible y espacialmente explícita para acercar la planificación a la gestión y mejorar el proceso de toma de decisiones (Mäkelä and Pekkarinen, 2004). Una situación parecida se da en los proyectos de mitigación de emisiones de gases de efecto invernadero a través de actividades de forestación y reforestación bajo los esquemas y estándares del Mecanismo de Desarrollo Limpio (UNFCCC, 2013) y el Verified Carbon Standard (VCS) (VERRA, 2019). Estos proyectos necesitan monitorear periódicamente las existencias de carbono de la vegetación plantada para cuantificar las emisiones evitadas; normalmente cada 5 o menos años.

La mayor disponibilidad de datos de bajo coste, como los generados periódicamente por sensores remotos, es un aliciente para la búsqueda de métodos de actualización continua de los inventarios. Por ejemplo, en los últimos años se han usado datos ALS para caracterizar

la estructura de la vegetación de forma continua y precisa en inventarios operacionales de numerosos países (Næsset, 2014). Además, muchos de estos inventarios se llevan a cabo utilizando datos ALS de campañas nacionales o regionales (Noordermeer et al., 2019), lo cual reduce notablemente los costes. Por otra parte, como se menciona en el apartado 1.4, la DAP se ha utilizado con resultados comparables al ALS para la estimación de variables de inventario, y pueden aprovecharse con este fin datos capturados por campañas nacionales o regionales de adquisición de imágenes aéreas, las cuales se realizan en muchos países en intervalos más cortos que las de ALS (Stepper et al., 2014b). De esta forma, si se hicieran coincidir las fechas de inventario con las campañas de adquisición de imágenes aéreas y datos ALS, se podrían actualizar los inventarios en periodos de muy cortos, uniendo así la información adquirida con los objetivos de gestión a partir de inventarios dinámicos de alta resolución espacial y temporal. Sin embargo, inventariar los montes en periodos más cortos es económicamente inviable debido a que los costes del trabajo de campo representan una parte importante del total en los inventarios asistidos por información 3D mediante métodos de masa (Eid et al., 2004). Según la experiencia de Agresta S. Coop., que ha levantado alrededor de 4000 parcelas de inventarios basados en ALS desde 2014, los costes del muestreo de campo suponen más del 40% del total de los costes.

Es posible conocer el estado de la masa en un momento intermedio entre dos inventarios a partir del estado actual utilizando modelos de crecimiento (Kangas et al., 2014). De esta forma, se puede conseguir aumentar la durabilidad de los datos 3D reduciendo los costes de inventario mediante el uso de modelos de crecimiento para predecir las estimaciones de variables dasométricas a nivel de celda cuando se utiliza métodos de masa (Härkönen et al., 2013; Tompalski et al., 2018). Sin embargo, los modelos de crecimiento no están disponibles para todas las especies y, cuando lo están, suelen ser válidos sólo para las zonas más productivas, especialmente en los países mediterráneos (Barreiro et al., 2016). Por otra parte, aunque las claras o las cortas finales pueden ser planificadas en base a modelos de crecimiento, éstos son la principal fuente de incertidumbre en este tipo de gestión (Holopainen et al., 2010). Por último, hay que significar que, si bien estos modelos son útiles para conocer el crecimiento e incluso predecir claras y cortas (Barreiro et al., 2016), no aportan información acerca de perturbaciones naturales que originen cambios en la masa.

1.8 Transferibilidad de modelos

Además de la mejora en la resolución espacial de los datos 3D, una posible solución económicamente viable para reducir la incertidumbre debida al uso de modelos de crecimiento en la gestión forestal puede ser el desarrollo de modelos transferibles basados en variables robustas y estables. El uso de estos modelos puede contribuir a reducir los altos costes de adquisición de datos de campo en cada inventario asistido por datos remotos (Görgens et al., 2015). La transferibilidad es un objetivo clave en el desarrollo de muchos modelos, pudiendo ser ésta de diferentes tipos. Los dos casos más normales en los que se estudia la transferibilidad de modelos son (i) cuando éstos se transfieren a nuevos datos adquiridos en la misma zona en otro momento (transferibilidad temporal) y (ii) cuando los modelos se ajustan utilizando datos de una zona y son aplicados en una nueva zona (transferibilidad espacial). En ambos casos, para asegurar la transferibilidad de los modelos se tiene que cumplir, entre otras premisas, que los datos con los que se han entrenado los modelos cubran el rango de variabilidad de la estructura de la vegetación presente en los nuevos datos (Fekety et al., 2015).

La transferibilidad temporal de modelos basados en datos 3D puede permitir no sólo detectar y monitorizar grandes cambios en la vegetación debidos a cortas finales, fuegos o derribos masivos, sino pequeñas variaciones causadas por el crecimiento o actuaciones selvícolas como las claras (Fekety et al., 2015). Por otro lado, la transferibilidad espacial de modelos permite, por ejemplo, utilizar datos de otros inventarios para estudiar variables forestales en áreas donde no hay datos de campo o donde no es rentable tomarlos (Stepper et al., 2017). La disponibilidad de datos de campo y de sensores remotos multitemporales o de diferentes áreas puede ser aprovechada, además, para generar “modelos agrupados”, es decir, combinar todos los datos para crear modelos robustos basados en un número mayor de parcelas y datos remotos (Fekety et al., 2015; Noordermeer et al., 2019).

Cabe destacar que la transferibilidad espacial o temporal directa de los modelos no está garantizada debido a que, aunque el sensor utilizado sea del mismo tipo y las especies estudiadas y su estructura también lo sean, las diferencias en la configuración del vuelo o de los parámetros del sensor afectan a las características finales del dato. Vuelos ALS a diferentes alturas y/o con distintos parámetros de escaneo pueden producir nubes de puntos con distintas densidades y, más importante, con distintas distribuciones de los pulsos (Bater et al., 2011; Keränen et al., 2016). Lo mismo sucede cuando se usan datos fotogramétricos generados a partir de imágenes con distinto solape, *ground sample distance* (GSD) o distancia focal (Kirchhoefer et al., 2019). Por ello, es preciso encontrar

estadísticos estables para generar modelos que puedan ser transferidos a nuevos datos remotos (Görgens et al., 2015) y validar los resultados cuando se usan modelos transferidos para asegurar que las predicciones no son sesgadas.

Finalmente, contar con diversas fuentes de datos como ALS y DAP permite aumentar enormemente la resolución temporal de los datos remotos, lo que conduce a cuestionar si es posible construir modelos de predicción de variables dasométricas que puedan ser utilizados indistintamente en ambas tecnologías. Este tipo de transferibilidad puede permitir aplicar modelos generados a partir de un único inventario de campo a los datos 3D adquiridos sucesivamente, independientemente de la naturaleza del origen de los mismos. De esta forma, cuando existe un DTM generado a partir de ALS, la transferibilidad de modelos puede ser de gran interés para propietarios y gestores forestales debido a la reducción de las necesidades de datos de campo (Fekety et al., 2015; Tompalski et al., 2019), y supone una oportunidad para desarrollar métodos de inventarios continuos y dinámicos que aproximen la planificación a la gestión forestal de precisión.

1.9 Objetivos y preguntas de investigación

El objetivo principal de esta tesis es evaluar la capacidad de la DAP para estimar variables forestales relevantes para la gestión forestal y el monitoreo de carbono desde diferentes plataformas.

Este objetivo se aborda a través de las siguientes preguntas de investigación:

1. *¿Qué similitudes y diferencias tienen las nubes de puntos generadas mediante DAP y ALS?*
2. *¿Pueden usarse imágenes aéreas de campañas nacionales como el PNOA como fuente de datos alternativa a ALS en la estimación de variables de inventario?*
3. *¿Es posible generar modelos que sean transferibles entre datos 3D tomados con la misma tecnología y diferentes características? ¿Y usando ALS y DAP indistintamente?*
4. *¿Puede calcularse la biomasa aérea en parcelas de muestreo mediante métodos de árbol individual a partir de imágenes de UAV?*
5. *¿Mejora las estimaciones de biomasa aérea utilizar datos satelitales radar y multiespectrales como información auxiliar?*

1.10 Estructura de la tesis

Esta tesis se compone de tres bloques que quedan resumidos en la tabla 1.1 y está estructurada en 6 capítulos. En el Capítulo 1 se expone una introducción general de la tesis. Los capítulos 2, 3 y 4 reproducen completamente artículos originales de investigación que han sido publicados en revistas que figuran en los listados *Journal Citation Reports (JCR)* y *Scopus* en posiciones Q1 o Q2 (Capítulos 2 y 4) o se encuentran en fase de revisión (Capítulo 3). Estos capítulos, redactados en inglés, responden a las preguntas formuladas en el apartado anterior. Finalmente, en el capítulo 5 se presenta una discusión general de la tesis, y en el capítulo 6 se enumeran las conclusiones generales.

En el Capítulo 2 se resume un estudio que se llevó a cabo en masas de *Pinus pinaster* del Monte de Utilidad Pública Nº 39 de la Comunidad de Madrid y sirve como una primera aproximación al uso de la fotogrametría digital aérea en el inventario forestal. En primer lugar, se comparan una nube de puntos DAP y otra ALS generadas a partir de vuelos del Plan Nacional de Ortofotografía Aérea (PNOA). Tras esto, se generan modelos no paramétricos utilizando estadísticos DAP y ALS para predecir 4 variables forestales, y finalmente se hace una comparación de los resultados obtenidos usando las dos tecnologías.

Tras observar las semejanzas y diferencias entre las nubes de puntos DAP y ALS, en el Capítulo 3 se analiza la posibilidad de construir modelos no paramétricos de volumen de madera que sean transferibles entre distintos datos 3D. Este estudio se realizó en masas de *P. sylvestris* del monte *Pinar de Valsaín* en Segovia y en él se utilizan datos ALS obtenidos con dos sensores diferentes y densidades de puntos diferentes y datos DAP de dos fechas distintas generadas a partir de imágenes aéreas de vuelos del PNOA con distintas configuraciones. El objetivo de este estudio es generar modelos de volumen que puedan ser transferidos temporalmente y entre distintos sensores con el fin de actualizar inventarios de forma económicamente viable.

Por último, en el Capítulo 4 se plantea un caso real de estudio de un monitoreo de carbono en un proyecto *Afforestation, Reforestation and Revegetation* bajo los estándares VCS en plantaciones jóvenes de manglar mediante el uso combinado de datos DAP generados a partir de imágenes UAV de bajo coste y datos satelitales radar y multiespectrales de Sentinel-1 y Sentinel-2. Este estudio propone una metodología novedosa para la estimación de la biomasa aérea de este tipo de plantaciones a partir de un proceso semiautomático de detección y medición de diámetros de copas y alturas de los árboles dentro de las parcelas usando datos DAP generados a partir de las imágenes de muy alta resolución que

ofrecen los UAV. En este caso de estudio se utiliza la DAP como herramienta para tomar los datos de campo a partir de métodos de árbol individual y se usan los datos satelitales como información auxiliar para construir modelos de predicción dentro de un marco de inferencia basada en el diseño utilizando los estimadores del model-assisted.

Table 1.1 Resumen de contenidos de los capítulos 2, 3 y 4 de esta tesis.

Capítulo y resultado	Objetivos generales	Método y plataforma	Área de estudio
Capítulo 2. Navarro et al. (2018) International Journal of Remote Sensing	Comparar las nubes de puntos obtenidas usando DAP a partir de imágenes aéreas del PNOA con los datos ALS de PNOA. Evaluar si la combinación de DAP y DTM generado con ALS puede ser una alternativa a ALS en la estimación de variables de interés forestal.	Método de masa Aerotransportado <i>Pinus pinaster</i> Ait.	Sistema central (España)
Capítulo 3. Navarro et al. (En revisión) International Journal of Applied Earth Observation and Geoinformation	Analizar la transferibilidad de modelos de volumen entre: (1) datos ALS con distintas características, (2) datos DAP de distintos años y con diferentes resoluciones, y (3) datos ALS y DAP.	Método de masa Aerotransportado <i>Pinus sylvestris</i> L.	Sistema central (España)
Capítulo 4. Navarro et al. (2019) Remote Sensing	Analizar la capacidad de los datos DAP generados a partir de imágenes de UAV para detectar y medir variables de árbol individual. Estudiar la posibilidad de utilizar datos radar y multiespectrales como información auxiliar para estimar la biomasa aérea mediante inferencia basada en el diseño.	Árbol individual UAV Plantación joven de manglar (<i>Rhizophora mangle</i> L.)	Deltas de los ríos Salum y Casamanza (Senegal)

Capítulo 2. Testing the quality of forest variable estimation using digital aerial photogrammetry: a comparison with airborne laser scanning in a Mediterranean pine forest

Este capítulo reproduce el texto del siguiente manuscrito:

Navarro, J.A., Fernández-Landa, A., Tomé, J.L., Guillén-Climent, M.L., Ojeda, J.C., 2018. Testing the quality of forest variable estimation using dense image matching: a comparison with airborne laser scanning in a Mediterranean pine forest. *Int. J. Remote Sens.* 39, 4744–4760. <https://doi.org/10.1080/01431161.2018.1471551>

Abstract

Airborne laser scanning (ALS) is commonly used in forest mapping. Full coverage of ALS is already available in some countries to provide high-detailed terrain elevation models. These kinds of data sets have been shown to offer great potential in forest mapping. However, it presents some drawbacks such as the resampling periods may be longer than recommended for forestry purposes or unexpected data updates. The recent development of image matching algorithms makes digital aerial photogrammetry (DAP) point clouds an alternative to ALS in forest monitoring and management. Area-based approach estimations from ALS and DAP-based point clouds in a *Pinus pinaster* Ait. forest of Central Iberia were compared. Heights from image matching were normalized by an ALS-derived digital terrain model (DTM). A total of 50 sampling plots were used to fit non-parametric models for the estimation of forest structure variables. Plot-level validation revealed that DAP-based models predicted dominant height, stem number, basal area, and growing stock volume with root mean square error of 10.71%, 43.02%, 27.02%, and 26.80%, respectively. The corresponding results from ALS data were 11.06% for dominant height, 39.71% for stem number, 25.07% for basal area, and 25.60% for growing stock volume. This study demonstrates the usefulness of the combination of DAP with ALS-derived DTM to develop forest metrics and high-quality inventories in Mediterranean pine forests.

Keywords: *image matching; photogrammetry; LiDAR, forest mapping; area-based approach*

2.1 Introduction

Airborne laser scanning (ALS) is a powerful technology that enables an accurate characterization of vegetation structure and it has been currently incorporated as an operational technology in forest mapping (Næsset 2002, 2004; Holmgren et al. 2003; Hall et al. 2005; Maltamo et al. 2005; Hollaus et al. 2007). For the last two decades, the emphasis has been focused on the development of methods for operational forest mapping that exploit the capability of ALS to provide continuous data (Maltamo, Næsset, and Vauhkonen, 2014). The most common method on ALS forest mapping is the area-based approach (ABA), which is based on statistical relationship between ALS metrics used as predictor variables and co-located ground plot measurements (Hawbaker et al. 2010; Holmgren et al. 2003; Järnstedt et al. 2012; Lim et al. 2003; Næsset 2002). The predictive models derived from field plot data are then applied to wall-to-wall estimate the main forest mapping variables (White et al. 2013).

Due to its potential applications, there is an increasingly number of countries developing national programs to capture ALS data (e.g. Netherlands, Sweden, Austria, Slovakia, Finland, Czech Republic, Switzerland or Denmark). In this sense, forest inventories based on nationwide ALS datasets offer a great opportunity for reducing costs (González-Ferreiro, Diéguez-Aranda, and Miranda 2012).

In the case of Spain, the National Mapping Agency of Spain (IGN in its Spanish acronym) has finalized a complete ALS coverage within the Spanish National Plan of Aerial Orthophotography (PNOA; Ministry of Infrastructures and Transport 2017) with a mean point density of 0.5 pulses m^{-2} . This ALS data is open access without any charge for users and is expected to be updated every six years, although the update periods depend on national and regional governments funding. The vegetation could suffer changes due to storm or snow damages, wildfires or harvesting along the gap between flight campaigns, therefore updated information is required to detailed follow up on the forest stands (Holopainen, Vastaranta, and Hyypä 2014; Näsi et al. 2015). The situation in many of the countries which are collecting ALS data for DTM mapping or other purposes is similar; updating periods are long or data update is not expected.

The need to improve temporal resolution in accurate height estimation and forest structure characterization has led to the search for alternative technologies (Holopainen et al. 2015). In recent years, the development of digital aerial photogrammetry (DAP) due to significant improvements in hardware and algorithms, such as Structure-from-Motion (SfM) has fostered image-based digital surface models (DSM) generation (Gehrke et al. 2008; Remondino et

al. 2014). Thus, ALS-like point clouds may be produced by photogrammetric matching of digital aerial images (White et al. 2013; Pitt, Woods, and Penner 2014). DAP-based point clouds only provide information above top surface, so an accurate bare-earth digital terrain model (DTM) for estimating canopy height and structure is essential (Vastaranta et al., 2013). Therefore, ALS data can provide highly detailed ground DTMs in forest areas (Baltsavias, 1999) and tree heights might be measured accurately if DAP-based point clouds are normalized by subtracting the ALS-based terrain elevation (Bohlin et al., 2012; Järnstedt et al., 2012; Pitt et al., 2014; Puliti et al., 2015; St-Onge et al., 2004). In order to carry out this methodology, high spatial resolution and vertical accuracy for DTM is required (White et al. 2013). The specifications to get an adequate image-based point cloud are: (i) multiple aerial overlapping images with high spatial resolution, (ii) high overlap between images to get a multi-view matching and reducing the impact of occlusions that are common in the forest canopy (Baltsavias et al., 2008; Haala et al., 2010; Leberl et al., 2010). In Spain, the IGN acquires stereo-images during regular nationwide campaigns within PNOA program. PNOA aims to obtain digital aerial orthophotos with 25 and 50 cm resolution of the whole Spanish territory, with an update period of 2 to 3 years according to the different zones. Therefore, the cycle of image acquisition is shorter than nationwide ALS. Since ALS-derived ground data is available for the whole Spanish territory, forest information may be updated periodically using image-based point clouds. This assumption can be extrapolated to other countries where photogrammetric flights are more frequent due to the need of higher altitudes and flying speeds relative to an ALS survey (Leberl et al. 2010).

In this sense, studies that estimates forest attributes generated from large frame image based DSM are found in the literature. Järnstedt et al. (2012) found that DAP has a great potential for estimating forest variables such as diameter, basal area, mean height, dominant height, and volume resulting in comparable accuracy to ALS-based estimates for the same area in Finland. The research developed by Bohlin et al. (2012) predicted tree height, growing stock volume, and basal area for forest stands using DAP canopy height in Sweden with similar accuracies than the ones obtained with ALS-based methods. Similar results were found by Vastaranta et al. (2013) and Nurminen et al. (2013) in Finland test areas. Rahlf et al. (2014) fitted linear mixed effects models with vegetation height and density metrics obtained from DAP data to estimate growing stock volume in a Norway forest. A semi-individual tree crown approach was used by Rahlf et al. (2015) to evaluate different forest variables from Norwegian National Forest Inventory sample plots and DAP. More complex structured forest were studied by Straub et al. (2013). These authors demonstrated that DAP could be an alternative to ALS data for forest attributes estimations in Germany, even in mixed forests with a complex structure. Magnussen et al. (2016) studied the capabilities of DAP in the Northern Black Forest. Ginzler and Hobi (2015) used digital aerial

photogrammetry to create a DSM covering the whole of Switzerland in the Framework of the Swiss National Forest Inventory. Stepper, Straub, and Pretzsch (2015) used DAP to model growing stock in a highly structured broadleaf-dominated forest in southern Germany. Even, studies based on forest attributes estimations from unmanned aerial systems (UASs) DAP-based point clouds were analyzed (Fritz, Kattenborn, and Koch 2013; Lisein 2012; Puliti et al. 2015).

Although the work developed is extensive, as far as we know, there is a lack of studies focused in Mediterranean pine forest of the central Iberian Peninsula. The big advantage of getting free available imagery covering large areas provides the opportunity to test DAP methods and ABA in this type of forest stands. According to White et al. (2013), more research is needed to demonstrate the ability of DAP-based point clouds and ABA to predict forest attributes in a wide range of forest types.

The aims of this study are: (1) generating DAP-derived point clouds from PNOA imagery and comparing it with PNOA ALS data; (2) estimating common forest attributes such as dominant height, basal area and growing stock volume at the plot-level using nonlinear regressions and ABA; and (3) comparing results of ALS and DAP estimations in order to evaluate if the combination of DAP-based point clouds with ALS-derived DTMs may be an alternative source of data to measuring forest variables in mountain Mediterranean pine forest ecosystems.

2.2 Materials

2.2.1 Study area

The study area is a 1,926 ha maritime pine (*Pinus pinaster* Ait.) managed forest located in an area called "Pinar y Agregados", in northern Madrid region, Spain (40°40'N, 4°7'E) (Figure 2.1). Stands are mainly even aged and single layer. The topography is generally undulating or steep terrain ranging from 930 m to 1,565 m elevation, with an average slope of 15.9° (standard deviation = 7.2°).

Figure 2.1 Location of test site in northern Madrid region (Spain) and spatial distribution of field plots.

2.2.2 Remotely sensed data

Both ALS information and aerial images were captured simultaneously the 9th November 2016 and were provided by PNOA (Ministry of Infrastructures and Transport 2017). The flight altitude was 3,600 m above mean ground level, with a speed of 150 knots. The sensor used for aerial images acquisition was a Leica RCD30 sensor (Leica Geosystems AG, Heerbrugg, Switzerland). The aerial images were acquired with an average stereoscopic forward overlap of 70% and side overlap of 60%. Imagery consisted in a set of 22 images with

panchromatic, red (R), green (G), blue (B), and infrared bands (IR). The ground sample distance (GSD) was approximately 0.35 m.

ALS information was captured using a Leica ALS50 system (Leica Geosystems AG, Heerbrugg, Switzerland) with a mean density of 2.96 points/m² and vertical $RMSE \leq 0.20$ m. ALS sensor had a pulse repetition rate of 79 kHz, a maximum scan angle of 36°, and an overlap of 25%. ALS tiles were processed with FUSION software (Mcgaughey and Carson, 2003). A 2-meter resolution DTM was generated by assigning the mean height value of ground returns within the cell to each cell. This cell size was chosen because is a common resolution when using nationwide low-density ALS data.

2.2.3 Field sampling

Field survey was carried out in 2013 by Agresta Sociedad Cooperativa trying to encompass the range of structural and ecological variability in the area. For this purpose, height and tree cover ALS-derived statistics were generated in a 25x25 m grid using the 2010 PNOA's ALS data to identify vertical and horizontal forest structural variability. In order to characterize these differences, three parameters defining vertical and horizontal forest structure were combined in a unique code (Table 2.1) and evaluated in each 25x25 m pixel: (i) 90th height percentile (h_{90}), (ii) canopy cover (CC_2) as percentage of first returns above 2 m and (iii) a canopy ratio (CR) defined as is shown in equation (2.1).

$$CR = \frac{h_{90} - h_{20}}{h_{90}} \times 100, \quad (2.1)$$

Where h_{90} and h_{20} are the 90th and 20th height percentile, respectively. Selection of statistics was based on the company experience.

A total of 50 circular sampling plots of 625 m² were established encompassing the structural variability of the area through the generated code.

Field plot center was located using a Trimble R10 device (Trimble Navigation Ltd., Sunnyvale, Calif., USA) and a Trimble R6 as base station. For Real Time Kinematic corrections Trimble Virtual Reference Station and the IGN Global Navigation Satellite Systems reference station network were used. When no mobile coverage was available, the locations were post-processed. Plot position was established with an average error of 0.2 m.

Table 2.1 Parameters measured in each 25 × 25 m pixel to generate a code characterizing the vegetation structure of the study area.

Parameter	Class value	Code (new value)
CC ₂ (%)	10–40	100
	40–70	200
	70–90	300
	>90	400
h ₉₀ (m)	0–12	10
	12–16	20
	16–20	30
	>20	40
CR (%)	0–33	1
	33–66	2
	>66%	3

Measurements of dbh (diameter at breast height) ≥ 7.5 cm and height were recorded from every tree in the field plots. Based on the single tree estimates of diameter and stem height, dominant height (H_o), stem number (N), basal area (G) and growing stock volume (V) were computed for each field plot (Table 2.2). Growing stock volume was estimated using stem taper equations implemented in cubiFOR (Rodríguez, Broto, and Lizarralde 2008).

Table 2.2 Summary of the field plot parameters ($n = 50$).

Parameter	Minimum	Mean	Maximum	Standard Deviation
H_o (m)	6.70	14.78	21.20	3.35
N (ha ⁻¹)	16.01	414.04	1088.73	243.16
G (m ² ha ⁻¹)	6.34	32.94	75.38	15.96
V (m ³ ha ⁻¹)	26.20	232.20	558.01	129.67

H_o = dominant height, N = stem number, G = basal area, V = growing stock volume

2.3 Methods

2.3.1 DAP-based point cloud

The Agisoft Photoscan Professional Edition 1.2.3 (64 bit) software (Agisoft LLC, 2016) was used to generate dense image-based point clouds. Photoscan uses proprietary algorithms based on computer vision Structure-from-Motion (SfM) and stereo-matching algorithms to align images and build a sparse point cloud. After initial alignment the position of the sparse point cloud was optimized using the bundle-adjustment algorithm implemented by Photoscan. In the next step, a dense point cloud was created by using multiview stereo-reconstruction algorithms. For this study, medium quality reconstruction and *Mild* depth filtering was chosen as it is recommended when the geometry of the scene is complex with numerous small

details (Agisoft LLC, 2016). The point cloud was georeferenced to the ETRS89 UTM Zone 30N coordinate reference system.

The resulting dense point cloud was exported to LAS format files in tiles of 1x1 km, with x, y, and z coordinates and RGB information. Processing was performed on an Intel Core i7 CPU, 4GHz with 4 cores and 32GB memory.

2.3.2 Forest structural metrics

The ALS and DAP-based point clouds were normalized by subtracting the ALS DTM from the Z coordinate of each point. A total of 25 metrics of normalized ALS and DAP point clouds for each field plot were computed using a threshold height of 2 meter to separate trees from understory vegetation (Næsset, 2002a). These metrics correspond to maximum, minimum, mean, variance, standard deviation, variation coefficient (h_{cv}), interquartile range, kurtosis, percentiles (ranging from the 1th to 99th percentile: h_{01} , h_{05} , h_{20} , h_{25} , h_{30} , h_{40} , h_{50} , h_{60} , h_{70} , h_{75} , h_{80} , h_{90} , h_{95} and h_{99}), canopy relief ratio, median of the absolute deviations from the overall mode of height (*Elev.MAD.mode*) and percentage of all points above mean. Forest canopy cover was also estimated for ALS data as the ratio between the number of first returns above 2 m and the total number of first returns. In the case of DAP-derived point cloud this parameter corresponds to the percentage of all points above 2 m. The canopy relief ratio describes the relative canopy shape from altimetry observation (Pike and Wilson, 1971). This ratio reflects the degree to which canopy surfaces are in the upper (> 0.5) or lower (< 0.5) portions of the height range (Parker and Russ, 2004).

2.3.3 Comparison of DAP and ALS-derived point clouds and metrics

A quality assessment of the DAP-based point cloud was conducted by comparing it with the ALS-derived point cloud at the plot level. This task was performed using the *CloudCompare* software (Girardeau-Montaut, 2014). If the reference point cloud is not dense enough, such as our ALS data, developers of *CloudCompare* recommend to locally modeling the reference cloud surface. Thus, the distance between two nearest points in both point clouds is replaced by the distance of the point in the compared cloud to this model (Girardeau-Montaut, 2015). Cloud to cloud distance was computed using a 6 parameters quadratic function. The computed distance was split along its X, Y and Z components in order to assess vertical differences between ALS and DAP point clouds. For a more reliable comparison, only first pulses from ALS point cloud were used since DAP is not able to penetrate below the canopy.

In addition, a 0.5 m resolution canopy height model (CHM) for each point cloud was generated. These CHM was created by subtracting bare earth heights from the DSM heights. The highest values of the CHM were extracted and compared between both datasets.

2.3.4 Area-based modelling of forest attributes

Random Forest (RF) (Breiman, 2001), a non-parametric regression algorithm, was used was adjusted to model the relationship between ALS and DAP-derived data with the four studied forest attributes (H_o , N , G and V). RF is a machine learning technic based on the ensemble of many decision trees, which has become one of the most common technique in remote sensing analysis (e.g. Gleason and Im 2012, Hudak et al. 2012, Ahmed et al. 2015). For each individual decision tree, data is randomly segregated in two data sets for training and validation. The procedure used in the random generation of decision allows low correlation between the individual decision trees, ensuring robustness in the RF results. Several advantages have been observed comparing RF with other machine learning alternatives, such as the capacity for working with numerous predictor variables, the lack of overfitting problems and robustness with respect to noise in the data. RandomForest package (Liaw and Wiener, 2002) was computed within R environment software (R Core team, 2015).

In order to achieve parsimonious models, VSURF package (Genuer et al., 2015) was used. This package allows a variable selection following three steps (i) to eliminate irrelevant variables from the dataset, (ii) to select variables related to the response, and (iii) to refine variable selection by eliminating redundancy in the set of variables selected in the second step for prediction purpose.

The out-of-bag (OOB) error statistic provided in RF shows the goodness of model fit, but not necessarily predictive performance. For this reason, an independent data withhold of 10% was performed for a more precise model validation (Evans and Cushman, 2009). A bootstrapping validation technique was followed by randomizing the independent data and executing RF model a thousand times. At each replicate a prediction to the withheld data was made. This cross-validation procedure was used by applying the Random Forest Classification or Regression Model Cross-validation tool (*rf.crossValidation*) implemented in the *rfUtilities* package (Evans and Murphy, 2015).

To determine the estimation accuracy of the different variable predictions examined in this study, the error was computed as the cumulative root mean squared error (*RMSE*) from each bootstrap. The relative *RMSE* was calculated as the percentage of the average *RMSE* value

for each forest attribute. The percentage of variance explained from bootstrap samples was included in the evaluation of the accuracy as an estimator of the goodness of fit.

2.4 Results

2.4.1 Comparison of DAP and ALS-derived point clouds and metrics

The average DAP point cloud density was 4.32 points m^{-2} , while the ALS pulse density was 2.96 points m^{-2} . Only 68.15% of ALS first returns were above 2 m in sample plots, while this percentage increases to 82.69% for DAP-derived point cloud. ALS and DAP-derived metrics were strongly correlated. The study yielded correlation higher than 0.87 for all percentiles (Table 2.3). Lower height percentiles were less correlated than higher percentiles and higher correlations were achieved from 50th height percentile.

Cloud to cloud distance computed for each plot gives a mean vertical difference between both point clouds (average $\pm$ standard deviation) of 0.02 ± 0.80 m taking as reference the ALS point cloud (Figure 2.2). A denser characterization of the top of canopy is presented by DAP point cloud. However, it is less sensitive to small gaps in canopy and tree top shapes than ALS point cloud (Figure 2.3).

Figure 2.2 Example of deviations between the DAP and the ALS reference point cloud (black points) in a sample field plot. Histogram on the right shows the distribution of vertical distances between the two point clouds for all sample field plots.

Table 2.3 Correlation matrix of ALS and DAP-derived height percentiles with a significance level of 0.05.

	Height percentiles	DAP metric						
		h_{01}	h_{10}	h_{25}	h_{50}	h_{75}	h_{90}	h_{99}
ALS metric	h_{01}	0.87***	0.81***	0.71***	0.60***	0.52**	0.45**	0.33**
	h_{10}	0.77***	0.95***	0.87***	0.78***	0.71***	0.65***	0.53***
	h_{25}	0.72***	0.91***	0.95***	0.92***	0.87***	0.82***	0.72***
	h_{50}	0.61***	0.82***	0.95***	0.98***	0.97***	0.95***	0.88***
	h_{75}	0.51**	0.70***	0.88***	0.95***	0.97***	0.98***	0.95***
	h_{90}	0.45**	0.63***	0.81***	0.90***	0.94***	0.98***	0.97***
	h_{99}	0.35**	0.53***	0.74***	0.84***	0.90***	0.95***	0.98***

*** $p < 0.0001$; ** $p < 0.001$

Agreement between the CHM's derived from DAP and ALS data can be observed in Figure 2.3. In overall, DAP heights were 1.45 m greater than ALS height. This difference is due to the inability of DAP to detect small gaps as it was shown in deviation of lower ALS heights of the scatterplot (Figure 2.4).

Figure 2.3 Comparison of the vertical profile of ALS (blue points) and DAP (orange points) point clouds along a transect line.

2.4.2 Area-based modelling

Individual RF models were generated for H_0 , N , G , and V using point cloud metrics extracted from ALS and DAP data. A selection of predictive variable was applied in a first step. A maximum of four explanatory variables were selected by the VSURF approach. All models included a canopy density metric and height metrics except for H_0 models and for DAP V model, which were built using only canopy height statistics. Percentage of first returns above 2 m was included only in ALS based models, while percentage of all returns above mean of heights was used in DAP models and also in ALS models.

The cross-validation of selected RF models revealed that errors with respect to the *RMSE* for studied variables were similar using ALS and DAP-derived data (Table 2.4). DAP data predicted H_o with a *RMSE* slightly lower than ALS data ($\Delta RMSE\% = -0.35\%$) while differences in relative *RMSE* values between ALS and DAP-derived RF models were more accused for *N*. The relative *RMSE* values for *N* were 3.31% points higher for DAP compared to ALS. Similar results were obtained for *G* and *V* models in both datasets. The relative *RMSE* of *G* and *V* were 1.96% and 1.20% points higher for DAP compared to ALS models.

Figure 2.4 Scatterplot of ALS against DAP heights based on CHMs. Greater deviation is shown in lower ALS height percentiles.

Table 2.4 Performance of dominant height (H_o), stem number (*N*), basal area (*G*), and growing stock volume (*V*).

Data source	Variable	% Variance explained	<i>RMSE</i>	<i>RMSE</i> (%)
ALS	H_o (m)	75.90	1.63	11.06
	<i>N</i> (ha ⁻¹)	53.36	164.42	39.71
	<i>G</i> (m ² ha ⁻¹)	72.78	8.26	25.07
	<i>V</i> (m ³ ha ⁻¹)	78.60	59.43	25.60
DAP	H_o (m)	77.32	1.58	10.71
	<i>N</i> (ha ⁻¹)	45.53	178.12	43.02
	<i>G</i> (m ² ha ⁻¹)	68.36	8.90	27.02
	<i>V</i> (m ³ ha ⁻¹)	76.51	62.22	26.80

Values of explained variance of selected RF models were also in the same order of magnitude using ALS and DAP-derived data (Table 2.4). The percentage of explained variance values for DAP-derived models ranged from 45.53% to 77.32%. Lower value of explained variance was achieved for *N*, while H_o model was able to explain the higher

amount of variance. Except for N , values of explained variance were all above 68%. Values of explained variance when using ALS were larger than for DAP for all models except for H_0 , where was 1.43 % better in favor of DAP.

The highest differences between DAP and ALS were achieved for N where ALS was able to explain 7.83% more variance.

2.5 Discussion

This study analyses the possibility of estimating forest variables using digital aerial photogrammetry techniques. Frequency of available data obtained using ALS sensors may not be enough to do a proper follow up on the forest stands where changes occur because of forest management or disturbances. Therefore, having alternative technologies that fit the lack of ALS data is a great step forward for forest management. Mainly in areas such as Mediterranean stands forest where there is no previous research in this sense.

The selected study area is optimal for this pilot study since simultaneously ALS and DAP data were available for this zone where a detailed field campaign was carried out measuring all the different variables needed for the study.

The results show that point clouds obtained by both methodologies are able to yield satisfactory results (Table 2.4), meaning that both techniques are suitable for estimating forest variables. However, it is important to note differences between them. To do this, a comparison between ALS and DAP point clouds was carried out. Previous studies have evaluated differences between both methods (Lisein, Pierrot-Deseilligny, Bonnet, & Lejeune, 2013; B St-Onge, Vega, Fournier, & Hu, 2008; Vastaranta et al., 2013; White et al. 2015), but none have been conducted using a low density ALS point cloud.

Point densities were different in both data sources. For DAP-based point cloud, point density ($4.32 \text{ points m}^{-2}$) was higher than for ALS data ($2.96 \text{ points m}^{-2}$). Height metrics were highly correlated for both acquisition techniques. Upper height percentiles reached correlation coefficients above 0.97. These results are in accordance with those obtained by St-Onge et al. 2008 for 95th percentile at 20x20 m grid. Lower percentiles showed the smallest correlation, this is because ALS is able to penetrate through the canopy representing vegetation below canopy surface, while with DAP is not possible. For the same reason, lower DAP height percentiles were better correlated to higher ALS percentiles. The crowns produced by DAP were wider, less defined and more smoothed than those obtained with ALS. Thus, there were gaps in the canopy which were undetectable by DAP (e.g. Jensen and Mathews, 2016; Thiel and Schmulius, 2017; Vastaranta et al., 2013; Wallace et al., 2016; White et al., 2015. Perhaps

for this reason, mean DAP-based CHM is greater than ALS model since gaps were not detected and a higher value appears in its place as it was shown in deviation of lower ALS heights of the scatterplot (Figure 2.4).

Figure 2.5 Scatterplot of observed against predicted values from the cross-validation for the studied variable models. Black circles for DAP predictions and grey points for ALS predictions. Black line shows the linear fit of the predicted and observed DAP-based values and grey line shows the linear fit of the predicted and observed ALS-based values.

The cross-validation shows that accuracies in terms of relative *RMSE* of DAP estimations in this survey were consistent with other studies (Table 2.5). In these surveys *RMSE* for H_o ranged from 7.3% to 18.2%, for G varied from 11.8% to 36.2%, and for V from 12.0% to 40.4%. In the study developed by Gobakken, Bollandsås, and Næsset (2015) a *RMSE* for N ranging from 28.6% to 43.7% was reported. Predictions of stem number, basal area, and growing stock volume were more accurate for ALS data as it also occurred in the other studies (Table 2.5).

By the other hand, Gobakken, Bollandsås, and Næsset (2015) showed H_o estimations slightly better for DAP compared to ALS as the current study.

Table 2.5 Results in terms of relative RMSE of other studies which used airborne laser scanning (ALS) and/or digital aerial photogrammetry (DAP) to estimate dominant height (H_o), stem number (N), basal area (G), and growing stock volume (V).

Researchers	DAP				ALS			
	H_o	N	G	V	H_o	N	G	V
Järnstedt et al. (2012)	18.2		36.2	40.4	11.8		27.9	31.3
Bohlin et al. (2012)	7.45		11.4	13.2				
Nurminen et al. (2013)				22.6				20.7
White et al. (2015)			37.68	36.87			35.4	33.24
Vastaranta et al. (2013)			23.6	24.5			17.8	17.9
Gobakken, Bollandsås, and Næsset (2015)	7.3-9.2	28.6-43.7	12.0-21.7	11.8-18.3	6.5-7.5	20.6-35.1	9.9-15.4	10.3-18
Rahlf et al. (2014)				31.4				19.4
Rahlf et al. (2015)*		46.0	25.0	30.0				
Current study	10.7	43.0	27.0	26.8	11.0	39.7	25.1	25.6

*Semi-individual tree crown approach was used

GSD (35 cm) used in this study is on the same order as those of most of country's nationwide photogrammetric campaigns. However, the overlap used is higher than in typical regional flights. In this sense, raising overlap could improve accuracies of variable predictions due to a higher probability of successful matches, as minimize the occlusion areas (White et al. 2013; Gobakken, Bollandsås, and Næsset 2015). Nevertheless, Bohlin et al. (2012) and Nurminen et al. (2013) didn't found big differences in forest variable estimation by increasing overlap and improving GSD. Results show that nationwide aerial data such as PNOA imagery may be used for forest monitoring with satisfactory accuracies.

DAP-based point clouds require a high resolution DTM for normalization. In open areas DTM can be obtained directly from DAP data, but in dense forest ALS-derived DTM are needed. If a quality DTM is available, DAP may be an alternative method (Pitt, Woods, and Penner 2014). Although the 2 m ALS-derived DTM used to normalize point clouds had lower resolution than DTMs used in the cited studies, results of forest variables estimation were in the same order of magnitude (Table 2.5). It is hoped that higher resolution DTMs will be able to help for more accurate height predictions. However, González-Ferreiro et al., 2012 suggest that for forest stand variable estimation, laser pulse density can be reduced to low densities (up to 0.5 pulses m^{-2}) without significant loss of information, at least for estimation of the following key stand variables: mean and dominant height, stand basal area, stand volume and stand biomass fractions. Therefore, ALS from PNOA or other nationwide providers may be used to normalize DAP point clouds.

Further research should focus on study how image-based and laser data may be used to detect forest change and make DAP a useful technology for forest monitoring. Future research is planned to automatize the detection of changes in vegetation from different remote sensing datasets. A high-resolution ALS-derived DTM was available for this study, but it does not apply in every case. Thus, estimation of forest variables using only DAP data must be studied to know in which circumstances this method can provide satisfactory results.

2.6 Conclusions

This study has demonstrated that, despite the differences between ALS and DAP point clouds, DAP provides results close to ALS in Mediterranean pine forest of Central Iberia when a high-resolution DTM is available. Aerial imagery from national campaigns may be used to estimate different forest attributes using ABA. Results of this study were of same order of magnitude as other similar studies carried out on various types of forest. Accuracy of DAP-based models depends on the availability of a precise DTM due to DAP lack of penetration capacity below the canopy. However, with an accurate DTM, DAP presents an opportunity to develop forest metrics and high-quality inventories in a cost-effective manner. In addition, the cycle of image acquisition is shorter for aerial imagery than for ALS, so DAP may be used in forest mapping when ALS is not updated.

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Capítulo 3. Assessing the transferability of airborne laser scanning and digital aerial photogrammetry derived growing stock volume models

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Abstract

Three-dimensional (3D) data from airborne laser scanning (ALS) and, more recently, digital aerial photogrammetry (DAP) have been successfully used to model forest attributes. While multi-temporal, wall-to-wall ALS data is not usually available, aerial imagery is regularly acquired in many regions. Thus, the combination of ALS and DAP data provide a sufficient temporal resolution to properly monitor forests. However, field data is needed to fit new forest attribute models for each 3D data acquisition, which is not always affordable. In this study, we examined whether transferability of growing stock volume (V) models may provide an improvement in the efficiency of forest inventories updating. We used two available ALS datasets acquired with different characteristics in 2009 and 2010, respectively, generated two DAP point clouds from imagery collected in 2010 and 2017, and utilized field data from two ground surveys conducted in 2009 and 2016-2017. We first analyzed the stability of point cloud derived metrics. Then three different Support Vector Regression models based on the most stable metrics were fitted to assess model transferability by applying them to other datasets in three different cases: (1) ALS-ALS, (2) DAP-DAP and (3) ALS-DAP. Some metrics were found to be enough stable in each case, so they could be used interchangeably between datasets. The application of models to other datasets resulted in unbiased predictions with relative root mean square error differences ranging from -4.34% to 2.98%. Results demonstrated that 3D-based V models may be transferable between point clouds of the same type as well as point clouds acquired using different technologies such as ALS and DAP, suggesting that DAP data may be used as a cost-efficient source of information for updating ALS-assisted forest inventories.

Keywords: Aerial images, ALS, Multitemporal, Model transferability, Dense image matching, Forest inventory update

3.1 Introduction

The availability of accurate and updated forest data is essential for improving sustainable forest management, promoting forest conservation policies and reducing carbon emissions from deforestation and forest degradation (REDD+). In the past two decades, three-dimensional (3D) remote sensing data have been frequently used to enhancing inventory systems. In this sense, technologies such as Airborne Laser Scanning (ALS) or more recently Digital Aerial Photogrammetry (DAP) have proven to be a clear-cut tool for characterizing forest structure in large areas and assessing main forest stand variables (Maltamo et al., 2014; Næsset, 2004, 2002a). Most forest variables, such as growing stock volume (V), can be predicted more efficiently, economically, and accurately applying these technologies than using traditional fieldwork-based forest inventory methods.

Operational forest inventories are mainly conducted using the area-based approach (ABA) (White et al., 2013a), which is based on statistical relationship between 3D remote sensing metrics used as predictor variables and co-located ground plot measurements (Næsset, 2002a). To date, ALS data is the 3D remote sensing technology most extended due to its potential to characterize vegetation structure accurately and the ability to penetrate through the crown canopy to produce accurate bare-earth digital terrain model (DTM) (Hall et al., 2005; Hollaus et al., 2007; Holmgren et al., 2003; Næsset, 2004). The use of ABA with ALS data has been widely studied (Hawbaker et al., 2010; Holmgren et al., 2003; Järnstedt et al., 2012; Lim et al., 2003; Næsset, 2002a). Although the cost of performing ALS flights has decreased considerably in recent years, in most cases it is not feasible to capture ALS data with high temporal resolution (annual or higher). In Spain, the second national ALS coverage is being carried out six years after the first one by the Spanish National Geographic Institute (IGN) within the National Plan of Aerial Orthophotography (PNOA; Ministry of Infrastructures and Transport, 2019). This temporal resolution of ALS data may not be enough to properly monitor forests condition, especially in areas with rapid forest growth and intense forest management.

In the last decade, DAP has gained interest for generating 3D point clouds (White et al., 2013b). In contrast to ALS, which can characterize the vertical vegetation structure through the canopy profile, DAP only provides information above top surface (White et al., 2015). Although Giannetti et al. (2018) demonstrated that V may be estimated accurately using metrics derived from raw unnormalized UAV photogrammetric data in boreal and temperate mixed forests, this approach has not yet been tested with DAP. For this reason, a co-located accurate ALS-derived DTM is required for estimating canopy height and structure (Vastaranta et al., 2013). The main advantage of DAP against ALS data is that

acquisition costs are significantly lower since data is recorded from greater altitudes at faster speeds (Goodbody et al., 2019; Leberl et al., 2010). Nationwide aerial imagery is normally updated more frequently than nationwide ALS. DAP has been successfully used with ABA to model forest variables in several recent studies in boreal, temperate and Mediterranean forests (Bohlin et al., 2012; Navarro et al., 2018; Nurminen et al., 2013; Puliti et al., 2017; Rahlf et al., 2015; Vastaranta et al., 2013).

The main costs in forest inventories assisted by 3D data are due to remote sensing and field data acquisition. Although the use of nationwide ALS or DAP data considerably reduces 3D data acquisition costs, it should also be necessary to reduce field work costs for optimizing forest management. Using models from previous inventories or other areas may decrease the costs of fieldwork by reducing the need for sample plot data (Karjalainen et al., 2018; Tompalski et al., 2019). Fekety et al. (2015) and Domingo et al. (2019) used bi-temporal ALS data to demonstrate the utility of temporal transferability of models. Fekety et al., (2015) used repeated ALS flights data to fit models by pooling field observations from 2009 and 2003. Transferability of models fitted using only 2003 or 2009 were also assessed by applying them to observations in 2009 and 2003, respectively. The relative root mean square error ($RMSE_{\%}$) for V imputations increased from 45% to 46% when 2003 model based was applied to 2009 ALS metrics and from 48% to 53% when the model based in 2009 data was used with 2003 ALS metrics. They concluded that the relationship between ALS metrics and field data were valid for both flights. Domingo et al. (2019) used multi-temporal low-density ALS data from the Spanish nationwide coverage to assess model temporal transferability for seven forestry attributes. They used ALS data from 2011 with a mean density of 0.64 points/m² and 2016 with 1.25 points/m². The Support Vector Regression (SVR) models developed to predict V showed good transferability. V model fitted using higher density ALS data and extrapolated to 2011 performed better than the one developed from 2011. The $RMSE_{\%}$ decrease from 27.42% for the 2011 model to 20.15% for the 2016 extrapolated one. Domingo et al. (2019) demonstrated that combining transferable models with single-tree growth methods was a successful way to reduce fieldwork efforts and accurately estimate forest attributes in two different dates.

Due to the unaffordable costs of frequent ALS data acquisitions and the low temporal resolution of nationwide ALS campaigns, where available, the transferability of models based on other 3D remote sensing data sources, such as DAP, must be studied to update forest inventories (Goodbody et al., 2019). Given the high correlation of ALS and DAP-derived height metrics (Navarro et al., 2018; White et al., 2013b), it is expected that DAP data might be used to update previously monitored forestry attributes from ALS area-based models. The integration of DAP and ALS point clouds in forest monitoring would require the

development of models which may be fully transferable between the two technologies. To the knowledge of the authors, only a few studies have evaluated the transferability of ALS-based models to DAP data. Filippelli et al. (2019) have recently demonstrated the potential of apply existing ALS-based models to DAP point clouds for estimating forest structure variables. The mean pulse density of ALS data used in this study was 1.87 pulses/m², while DAP data was derived from imagery with 0.30 m ground sampling distance (GSD) and approximately 60% forward overlap and 30% side overlap. They found a few metric combinations for which a relatively small intercept and slope *bias* were introduced when the ALS data was interchanged by DAP point clouds. Tompalski et al. (2019) also studied the transferability of ALS-based models to DAP data. They used imagery with a 0.30 m GSD and 60% forward and 20% side overlap. In this study, global ALS-derived models were developed for various attributes using three different modelling approaches and were then applied to the DAP data. The results showed that there was a good transferability of V model when the random forest (RF) approach was used. In this case, the transferred model predictions resulted in an increase of *RMSE%* of 2.39% and a relative *bias* (*bias%*) of -1.67%.

The use of DAP is increasingly widespread since the forest structure attributes estimations are comparable to those of ALS while the costs of acquisition are substantially smaller (Goodbody et al., 2019). Kangas et al. (2018) recommended to use DAP or ALS data depending only on the availability and cost of the data as the difference in accuracy is negligible for forest owners. In view of the increasing use of DAP in forest inventories, there is a need to study the possible transferability of models when using DAP data from different flight configurations and camera specifications. Stepper et al. (2017) studied the spatial transferability of RF models for a conifer- and a broadleaf-dominated area in Germany. Digital aerial imagery for the two studied areas were acquired using the same camera with a 0.20 m GSD and along-track/across-track overlaps of 75%/40% and 75%/30%, respectively. Training and test sites were covered by the same imagery, so transferability to point cloud data with different characteristics was not assessed. V models showed good transferability since predictions over test sites had comparable accuracies without bias increment when sample size was large enough. Kirchhoefer et al. (2019) fitted linear regression models to predict V using DAP data in three different areas and then transferred the models to each area. All studied areas were covered by aerial imagery acquired using different cameras, with the same GSD and overlaps at close dates. They found that canopy height metrics were the most robust and models using that metrics achieved accuracies similar to those obtained from 10-fold cross-validation when they were transferred to the other data sets.

In this study, we used different 3D datasets corresponding to ALS and DAP acquisition from the same area to identify stable metrics. These metrics were then used to create ALS- and

DAP-based transferable V models. The main objective of this research was to evaluate: (1) transferability of ALS-based models to ALS point clouds with different characteristics, (2) temporal transferability of DAP-based models to DAP point clouds with different characteristics, and (3) transferability of ALS-based models to DAP point clouds.

3.2 Material and Methods

3.2.1 Study area

This study was conducted in the Pinar de Valsain forest located in the North facing slopes of the Sierra de Guadarrama (Central Mountain Range of Spain, 40° 51' N, 04°01' W, 1260–1995 m). The area is a 7,622 ha public forest dominated by Scots pine (*Pinus sylvestris* L.) and managed for high quality timber production. Other tree species were represented, mainly Pyrenean oak (*Quercus pyrenaica* Willd) below 1400 m. Even-aged forest management based on natural regeneration have been applied since 1889 (Diaz-Balteiro et al., 2017). The topography is characterized by steep slopes, with 59% of the area having steep slopes over 30%. The climate is sub-Mediterranean, with a mean annual precipitation increasing with elevation and ranging from 720 mm to 1320 mm. Average minimum and maximum temperature ranges from -1 °C in January to 22 °C in July.

Figure 3.1 Location of Pinar de Valsain test site in Spain and spatial distribution of field plots.

3.2.2 Ground reference data

A total of 202 circular plots were established and monitored during fall-winter 2009/2010 by Blom Sistemas Geoespaciales, and a subset of 30 were re-measured between fall-winter 2016/2017 by Marino et al. (2018).

Field campaign, 2009

Field plots with a 13 m radius (530.9 m²) were allocated across the study area via a stratified systematic sampling design. Four strata were defined considering the growth stages. Plot centers were georeferenced using two Leica SR530 channels dual frequency receivers, one operating as a base station and the other as a rover field unit. The recorded global navigation satellite systems (GNSS) data were post-processed using the Base Station Network at IGN. At each plot, diameter at breast height (dbh) was measured for all trees with DBH ≥ 7.5 cm. Tree heights were measured with a Vertex hypsometer for the three dominant trees in each sample plot.

Field campaign, 2016

Field measurements were conducted in circular fixed-area sample plots with a 14.1 m (625 m²). Field plot locations were selected to cover structural variability according to prior forest inventory and ALS data. Areas with disturbance or management activities during the time lag between field inventory and ALS data acquisition were excluded when choosing plot locations. The plot centers were re-measured with differentially corrected GNSS measurements with sub-meter accuracy. A Trimble Geo 7x unit was used and recorded GNSS data were post-processed into submeter precision with correction data from the closest base station of the Agricultural Technological Institute of Castile and Leon (ITACyL; ITACyL, 2019). Tree dbh was measured with the same criteria as in 2009 inventory, and tree heights were measured with a Vertex hypsometer for 10 randomly selected trees per plot.

Estimation of growing stock volume on the plots

Tree height was estimated for the unmeasured trees on each plot by applying a generalized height–diameter model developed using data from all trees measured in the 2009 and 2016 field campaigns for which total height was recorded. The growing stock volume of each callipered tree was estimated using stem taper equations implemented in cubiFOR (Rodríguez et al., 2008).

Table 3.1 Descriptive metrics of stand V ($\text{m}^3 \text{ha}^{-1}$) corresponding to the sample plots.

Year	N plots	Minimum	Mean	Maximum	Standard Deviation
2009	202	83.0	406.1	1229.1	203.2
2016	30	137.2	389.8	706.6	188.5

3.2.3 Remotely sensed data collection and processing

3.2.3.1 ALS data

Two available ALS datasets were used (Table 3.2): one from a specific ALS flight performed over the entire study area in June 2009 and one from a nationwide ALS survey acquired in 2010 by PNOA (Ministry of Infrastructures and Transport, 2019). For the specific flight campaign, ALS data were acquired and pre-processing by Blom Sistemas Geoespaciales with an average pulse density of 4.5 points/ m^2 using a Leica ALS60 system (Leica Geosystems AG, Heerbrugg, Switzerland). The 2010 ALS data was captured using a Leica ALS50 system with a mean density of 0.5 points/ m^2 . ALS tiles were processed with FUSION software (Mcgaughey and Carson, 2003). Pulse return elevations were normalized to heights above ground by subtracting the elevation of the underlying DTM from each return height. DTM was generated from ground returns at 2 m resolution for 2009 and 2010 ALS data.

3.2.3.2 DAP data

Aerial imagery was acquired in August 2010 and September 2017 by IGN as part of the regular nationwide campaigns within PNOA programme. The 2010 data was acquired on 28 August 2010 using an UltraCam Xp camera (Vexcel Imaging GmbH, a Microsoft Company, Graz, Austria) with an average stereoscopic forward overlap of 65% and side overlap of 40%, whereas the 2017 survey was conducted on 13 September 2017 with a Leica DMC III camera with forward and side overlaps of 60 and 40%, respectively. Imagery consisted in a set of 88 (2010) and 35 (2017) images with panchromatic, red, green, blue, and infrared bands. In the current study, only panchromatic digital imagery was used. The GSD in 2010 and 2017 surveys was 0.22 m and 0.28 m, respectively.

The aerial images acquired were processed using Agisoft Metashape (Agisoft LLC, 2019) to generate 3D dense image-based point clouds. This software has been successfully used in many cases for forest inventory purposes (Dandois and Ellis, 2013; Filippelli et al., 2019; Giannetti et al., 2018; Jensen and Mathews, 2016; Ota et al., 2015; Panagiotidis et al., 2017; Puliti et al., 2017). Agisoft Metashape uses proprietary algorithms based on computer vision

structure-from-motion (SfM) and stereo-matching algorithms to align images and multi-view stereo reconstruction. Further details on the photogrammetric processing of the aerial imagery can be found in Navarro et al. (2018). The resulting point densities of the 2010 and 2017 datasets were 6.81 and 4.14 points/m² with an average spacing of 0.38 and 0.49 m, respectively. In addition to x, y, and z coordinates, color bands values were recorded. Both point clouds were normalized using the 2010 ALS-derived DTM.

Table 3.2 ALS and DAP acquisition parameters.

	ALS Specific 2009	ALS PNOA 2010	DAP 2010	DAP 2017
Date collected	June 2009	September to November 2010	August 2010	September 2017
Sensor	Leica ALS60	Leica ALS50	UltraCam Xp	Leica DMC III
Number of images	-	-	88	35
Pulse repetition rate (kHz)	93.3	49.2	-	-
Maximum scan angle (°)	~26	~28	-	-
Forward overlap (%)	-	-	65	60
Side overlap (%)	-	-	40	40
GSD (m)	-	-	0.22	0.28
Average pulse density (points/m ²)	4.5	0.5	-	-

3.2.4 Variable extraction

Plot-level canopy structure metrics were computed for both the ALS and DAP point clouds (Næsset, 2004, 2002a) using the FUSION software (Mcgaughey and Carson, 2003) and the lidR package (Roussel and Auty, 2019) within R environment software (R Core team, 2015). Laser echoes and DAP points with a height above the ground < 2 m were excluded to separate trees from understory vegetation (Næsset, 2002a). Canopy variables were divided into three categories: height, height variability and density metrics. Height metrics included height percentiles (ranging from the 1st to 95th percentile: p_{01} , p_{05} , p_{10} , ..., p_{95}), the maximum ($h_{\max}$), minimum ($h_{\min}$), mean (h_{mean}), variance (h_{var}), standard deviation (h_{sd}), variation coefficient (h_{cv}), interquartile range (h_{iq}) and kurtosis (h_{kur}) of ALS echoes and DAP point heights. Canopy density metrics included the cumulative percentage of the number of ALS echoes and DAP points found above fraction 1st, 2nd, ..., 9th from all points (d_1 , d_2 , ..., d_9),

canopy cover (CC_2), understood as the ratio between the number of first ALS echoes (all DAP points) above 2 m and the total number of first ALS echoes (all DAP points), and the percentage of first ALS echoes (all DAP points) above the mean height (CC_{mean}).

3.2.5 Growing Stock Volume Modelling

Three support vector regression models were constructed from ALS and DAP-derived data to evaluate the transferability of V models in three different situations. In the first case (ALS-ALS transferability), an SVR model was generated from the 2009 specific ALS flight data and applied to 2010 nationwide low-density ALS data in order to analyze the performance of ALS-based model transferability when the model is used with a lower point density ALS dataset. In the second case (DAP-DAP transferability), a model was created linking V and 2010 DAP-derived variables. This model was then applied to 2017 DAP data to assess the temporal transferability of DAP-based models when two DAP datasets with different GSD and overlaps are used. The third case (ALS-DAP transferability) consisted in applying nationwide ALS-based models to DAP data in order to investigate whether low-density ALS data may be used to create V models potentially transferable to other data sources, such as DAP, and across time. A schematic representation of the study design is shown in Figure 3.2.

Figure 3.2 Schematic diagram describing the followed methodology to asses temporal and source transferability of the different point cloud-based models.

SVR with radial kernel was chosen to model V since other studies have shown that this method outperformed other parametric and non-parametric methods for estimating forest attributes using ALS data (Domingo et al., 2018; Gleason and Im, 2012; Jakubowski et al., 2013; Joibary, 2013). Moreover, Jakubowski et al. (2013) recommended to use SVR when working with low-density data. SVR converts the multidimensional regression problem into a linear problem to predict one-dimensional variables by assuming that input data are separable in space (Mountrakis et al., 2011). To solve this problem, appropriate kernel functions are used to map the training data into a new hyperspace feature (Smola and Schölkopf, 2004). SVR are appropriate when the training sample size is small due to only using data located nearest to the hyperplane edge (i.e. support vectors) (Vapnik, 1995). SVR with a radial basis function kernel were computed using the R-Package *caret* (Jed Wing et al., 2016). Cost and sigma parameters were tuned using a two-layer grid search method and performing a 10-fold cross-validation repeated 10 times. The specified grid search ranged from 0.25-1000 and 0-1 for cost and sigma parameters, respectively.

The metrics extracted from point clouds are expected to be highly correlated and to suffer from highly multi-collinearity (White et al., 2015). In order to avoid poor performance of explanatory variables selection and to achieve parsimonious and easily interpretable models, a four-step feature selection was performed: (1) A correlation analysis based on Pearson's product moment correlation coefficients (r) was conducted. Any metrics with an $r > 0.8$ were removed from the data set. (2) The pair-wise Wilcoxon rank sum test with a significance level of 0.05 was used to find equivalent variables in training and transferred datasets for each of the three SVR models. Using explanatory variables with not significant differences between datasets is expected to maximize potential for ABA model transferability (Stepper et al., 2017). (3) Only one variable for each category described in section 3.2.4. (i.e. height, height variability and density metrics) were included in the models. Variable importance for each case was computed using *caret* and all measures of importance were scaled to have a maximum value of 100. The variables with the highest importance score within each category were included in the candidate models. (4) Selection of the best suited model was conducted by identifying the combination of variables which produced the lowest root mean square error (RMSE).

The performance of the three SVR models developed at plot level was evaluated by means of 10-fold cross-validation repeated 10 times. Based on cross-validation residuals, absolute and relative *bias* and RMSE were determined (equation (3.1) -(3.4), respectively).

$$bias = \frac{\sum_1^n (y_i - \hat{y}_i)}{n}, \quad (3.1)$$

$$bias_{\%} = \frac{bias}{\bar{y}} \times 100, \quad (3.2)$$

$$RMSE = \sqrt{\frac{\sum_1^n (y_i - \hat{y}_i)^2}{n}}, \quad (3.3)$$

$$RMSE_{\%} = \frac{RMSE}{\bar{y}} \times 100, \quad (3.4)$$

where n is the number of field plots y_i is the field measurement value for the same plot i , $\hat{y}_i$ is the predicted value for plot i , and $\bar{y}$ is the mean ground reference value over all sample plots. In addition, R^2 coefficient was used to evaluate the goodness of fit of the models.

The selected SVR models were transferred to new datasets for the three study cases. Models transferability was assessed by the R^2 , $RMSE$, $bias$ and relative $RMSE$ and $bias$ from observed and predicted values. The differences in accuracy between cross-validated and transferred models were assessed by calculating the mean differences in $RMSE_{\%}$ ($\Delta RMSE_{\%}$) and $bias_{\%}$ ($\Delta bias_{\%}$).

3.3 Results

Growing stock volume of the 202 training plots was regressed against the predictor variables computed from 2009 ALS, 2010 DAP and 2010 ALS datasets to assess model transferability in the three study cases. One variable related to canopy height metrics category and one variable belonging to the canopy density class were included in all models (Table 3.3). The SVR model developed for the DAP-DAP transferability case also included h_{cv} as a canopy height variability metric. The most selected metric was h_{mean} , which was used in all SVR models. h_{mean} had the highest importance for all cases and was the most stable variable between all datasets based on the pair-wise Wilcoxon rank sum test (Table 3.3) and the visual inspection of metrics distribution (Figure 3.3). CC_{mean} in ALS 2009 and ALS 2010, and d_5 in ALS 2010 and DAP 2017, were significantly different (Wilcoxon rank sum test, p -value = 0.01228 and p -value = 0.01886, respectively). Although these two metrics were not so stable between datasets, we included them in SVR models since they improve V estimates and showed only small differences in Wilcoxon rank sum test.

Figure 3.3 Boxplots showing the distribution of the variables used in SVR models for the different transferability cases.

Table 3.3 Comparison of metrics used in V modelling for the different transferability cases based on the results of the pair-wise Wilcoxon rank tests. * p -value < 0.05 indicating significant difference.

Transferability case	Datasets	Variables	p -value
ALS-ALS	2009 ALS – 2010 ALS	h_{mean}	0.3423
		CC_{mean}	0.01228*
DAP-DAP	2010 DAP – 2017 DAP	h_{mean}	0.9477
		d_1	0.8349
		h_{cv}	0.5298
ALS-DAP	2010 ALS – 2010 DAP	h_{mean}	0.7419
		d_5	0.9864
	2010 ALS – 2017 DAP	h_{mean}	0.8738
		d_5	0.01886*

The results of model performance and transferability are shown in Table 3.4 and Figure 3.4. Scatter plots of observed versus predicted V values in the training and validation datasets for each case are displayed in Figure 3.5.

Table 3.4 Summary of V model performance and transferability assessment for the three different cases (Training data is shown in bold).

Transferability case	Training and validation dataset	R^2	RMSE ($\text{m}^3 \text{ha}^{-1}$)	bias ($\text{m}^3 \text{ha}^{-1}$)	RMSE (%)	bias (%)
ALS-ALS	2009 ALS	0.79	93.10	7.72	22.93	1.90
	2010 ALS	0.77	96.16	28.68	23.69	1.69
DAP-DAP	2010 DAP	0.68	116.73	7.10	28.75	1.74
	2017 DAP	0.81	79.85	3.13	20.48	-0.80
ALS-DAP	2010 ALS	0.71	110.35	6.24	27.18	1.54
	2010 DAP	0.63	122.46	-0.61	30.16	0.15
	2017 DAP	0.77	89.01	0.28	22.83	-0.07

Figure 3.4 Growing stock volume modelling and transferability results in terms of RMSE%, R^2 and bias% for the three transferability cases. Black points show results from cross-validation and the rest of the points show results of transferred models to new datasets.

Figure 3.5 Scatterplot of observed against predicted values for the three transferability cases. Black points show the assessment of SVR models from the 10-fold cross-validation repeated 10 times using the training datasets. Grey points show the performance of transferred models to independent validation datasets. Red line shows the linear fit of the predicted and observed V values.

In ALS-ALS transferability case, SVR model was fitted using 2009 ALS data and extrapolated to 2010 ALS data using the same metrics and model parameters. Results showed that when the model was applied to metrics based on training dataset, V was predicted with slightly lower $RMSE$ than when the model was transferred ($\Delta RMSE\% = 0.76\%$). The difference in R^2 values between the fitted and extrapolated models was also small (0.02). The application of the model to 2010 ALS metrics did not produce a higher $bias$ value ($\Delta bias\% = -0.21\%$).

The temporal transferability of DAP-derived models was assessed in the DAP-DAP transferability case. An SVR model was fitted using 2009 DAP metrics as predictor variables and then applied to 2017 DAP dataset. Results showed that 2017 DAP predictions of V were

more accurate than predictions made using the training dataset. $RMSE\%$ and $bias\%$ decreased from 28.75% to 20.48% and from 1.74% to -0.80%, respectively. The R^2 value improved from 0.68 to 0.81 when the model was transferred to 2017 DAP dataset.

Results of ALS-DAP transferability case revealed that the fitted V model from 2010 low density ALS was transferable to 2010 and 2017 DAP datasets. When the model was applied to 2010 DAP dataset, a decrease in accuracy was showed although predictions were unbiased ($bias\% = 0.15\%$). The increase of $RMSE\%$ was 2.98% when 2010 DAP metrics were included in the 2010 ALS-fitted model, showing the lowest R^2 value (0.63). The ALS-DAP extrapolated models achieved the highest R^2 and the smallest $RMSE$ and $bias$ values when 2017 DAP metrics were used as predictors. The R^2 value in 2017 DAP was larger than in 2010 ALS and 2010 DAP. The difference in R^2 values between the fitted and the 2017 extrapolated model was -0.06. The relative $RMSE$ value for V was 4.34% lower for 2017 DAP compared to 2010 ALS, and $bias\%$ decreased from 1.54% to -0.07%.

3.4 Discussion

This study examined the transferability of models based on 3D point clouds using different data sources. We studied three possible situations in which it may be useful to apply models generated from a different data source. For this purpose, various models were adjusted using ALS and DAP data, and applied to point clouds of different characteristics or acquired at different time periods in the same study area. We modelled V in all cases because this variable is widely used in forest management. Results of this study revealed that it is not only possible to build V models which may be successfully applied to datasets of the same nature as training data, i.e. ALS-ALS or DAP-DAP, in different periods or with different characteristics (temporal transferability), but also to use models fitted using ALS metrics to estimate V values from DAP data (data source transferability).

We used SVR to predict V since it has been successfully used for temporal transferability of low density ALS-based models (Domingo et al., 2019). Although Tompalski et al. (2019) found a higher decrease in accuracy of transferred non-parametric models, this could be due to the lack of variable selection. To improve the transferability of the models in the three different cases, we proposed a variable selection looking for the most accurate model for V estimation in addition to identifying the most stable metrics. Unlike other studies, our models were built taking into account variables that were stable between the training dataset and the point cloud used to transfer the model (Domingo et al., 2019; Fekety et al., 2018, 2015; Tompalski et al., 2019). In addition, the variable selection allowed to generate parsimonious models and avoid unstable predictions produced by strong inter-correlations

of metrics (Bouvier et al., 2015; Latifi et al., 2010). Thus, although the selected models were the best to predict V from a single dataset, the transferability of the models was optimized without large loss of precision.

The most stable variables were those directly related to tree height. h_{mean} was included in all models because, in addition to being the most important variable to predict V in all cases, it was the most stable variable among datasets. This is consistent with Asner et al. (2012), who found that mean canopy profile height from a voxel-based ALS method was a consistent variable to predict aboveground biomass in a variety of tropical forest areas using a single universal ALS model. Nevertheless, Asner and Mascaro (2014) found that top of canopy height (i.e. average value of pixels from a 1.12 m resolution canopy height model) was a more consistent metric. Although canopy density metrics are more sensitive to variations in point clouds characteristics (Magnussen et al., 2012), we found that some metrics were enough stable to be used in transferable models. All models included a canopy density metric because despite being significantly different between training and validation datasets in ALS-ALS and ALS-DAP transferability cases, its inclusion improved the accuracy of V predictions. Model fitted for DAP-DAP transferability case using 2010 DAP data was the only one including a height variability metric (h_{cv}).

ALS-DAP transferability case evaluated the feasibility of applying models generated from ALS metrics to DAP-derived point cloud data. Both types of point clouds are very different due to the ability of ALS to penetrate through the canopy representing vegetation below canopy surface while DAP is not. As in previous studies, there was a strong correlation between the high height percentiles of ALS and DAP point clouds (Filippelli et al., 2019; White et al., 2013b). However, higher differences were found between ALS and DAP-derived height variability metrics; therefore, none of these metrics was selected in ALS-DAP transferability modelling. These results were in accordance with Filippelli et al. (2019), who found low correlations between ALS and DAP-derived height variability metrics. Filippelli et al. (2019) suggested that only higher height percentiles and metrics representing upper canopy density may be used in ALS-based model transferability to DAP data. Nevertheless, we found that h_{mean} and d_5 were enough stable (Table 3.3).

Although we did not seek to only fit the most precise models in each case, but to combine the prediction ability and transferability, the overall accuracy of models fitted was similar to previous studies (Järnstedt et al., 2012; Nurminen et al., 2013; Rahlf et al., 2014; Vastaranta et al., 2013). The estimation based on ALS metrics for ALS-ALS transferability resulted in a $RMSE\%$ of 22.93%, which is in line with other studies in pine forests of the Iberian Peninsula (Domingo et al., 2019; Montealegre et al., 2016; Navarro et al., 2018). While results for DAP-

based model in DAP-DAP transferability case were consistent with values reported by some authors, the $RMSE\%$ is 1.95% higher than findings reported by Navarro et al. (2018) in a *Pinus pinaster* Ait. forest in a nearby area. The validation of ALS-based model for the ALS-DAP transferability case showed worse results than the model built for ALS-ALS transferability model due to the variable selection process. Metrics used were selected to ensure good transferability to DAP data in spite of the trade-off in model precision.

Results of ALS-ALS transferability model showed a very slight decrease of accuracy. Thus, $RMSE$, $bias$ and R^2 values were in the same range as those found in the original fitting dataset. Contrary to results of Keränen et al. (2016), who found that applying V models to ALS point data from different configuration flights produced significantly more biased predictions, we did not find an increase in $bias$ when the model was transferred. These results support previous research (Domingo et al., 2019; Fekety et al., 2015; Tompalski et al., 2019), suggesting that small differences in explained variance and accuracy are produced by applying ALS-based V models to different ALS point cloud densities. Our results also agree with Jakubowski et al. (2013) and Ruiz et al. (2014), which demonstrated that point cloud density has a minimum effect on the quality of V models. However, differences in sensors used and flight altitude not only affect point density but derived metrics (Fekety et al., 2018). Thus, looking for steady metrics between different ALS acquisitions may improve model robustness.

In order to be able to successfully transfer models in time, it is necessary that, among other premises, the range of stand structure conditions remain constant (Fekety et al., 2015). We assumed that this condition was met in the whole area because it is a forest area sustainably managed, resulting in a wide range of forest structures with excellent regeneration of the species (Marino et al., 2018). Predictions of transferred model in DAP-DAP case were remarkably more accurate compared to those obtained from data used to fit the model. Although Bohlin et al. (2012) concluded that smaller GSD does not improve the estimation accuracy of forest attributes using ABA, this alone could not explain the marked improvement in the performance of the transferred model. The accuracy increase observed may be due to the greater plot size used in the 2017 field campaign. Increasing plot size has been demonstrated to improve accuracy of forest attributes estimations using ALS data (Næsset et al., 2015; Navarro-Cerrillo et al., 2017; Ruiz et al., 2014). Using larger plots has two beneficial effects: (1) minimize the negative effect produced by inaccurate field plot positioning (Gobakken and Næsset, 2008) and (2) reducing the “edge effect”, i.e. trees whose crowns (or portion of crowns) are within the plot boundaries whereas stems are outside, and vice versa, but may be included in 3D point cloud measurements. This effect may have been emphasized by the characteristics of point clouds based on DAP, which

detect tree crowns in a wider, less defined, and more smoothed way than those obtained with ALS (Navarro et al., 2018). Our results of DAP-DAP transferability case agree with Kirchhoefer et al. (2019) and Stepper et al. (2017), who found that predictive DAP-based models can be transferred to other DAP datasets without loss of accuracy.

Results of ALS-DAP transferability case showed that ABA models built using ALS data may be used with DAP point clouds in this kind of pine forest. This confirms that it is possible to use indistinctly some variables from ALS and DAP data (Filippelli et al., 2019). Moreover, predictions of V were even less biased when model was transferred to DAP data. Although there was a small loss of accuracy when 2010 DAP data were used, the performance of the transferred model was within the range of other studies (Rahlf et al., 2015; Vastaranta et al., 2013; White et al., 2015). On the other hand, the $RMSE\%$ value for model applied to 2010 DAP data was 1.41% higher compared to the model based on 2010 DAP data built in DAP-DAP transferability case. This denotes that there were small differences in the accuracy of V estimates between the model fitted using DAP data and the model fitted using ALS data and then transferred to a DAP-derived point cloud. When the model was applied to 2017 DAP data, the result was similar to that of DAP-DAP transferability case, although there was a slight decrease in precision in terms of R^2 and $RMSE$. As in DAP-DAP transferability model, the significantly better results may be due to the increase in the plot size.

This study was conducted using typical aerial imagery settings from national and regional campaigns. This confirms that DAP data generated from aerial images captured to produce regional orthoimages provides accurate V estimations using models based on the same DAP data, DAP data from another date or even using models based on ALS data. Although the highest precision was obtained in ALS-DAP transferability case when using 2017 DAP data, it is not possible to draw conclusions on how DAP-derived point cloud characteristics affect the transferability of V models since plot size used in both field campaigns was different. Future research must validate temporal model transferability using the same field plot size.

Multitemporal ALS incorporate the time dimension to 3D data allowing processes such as tree growth to be described (Eitel et al., 2016). The indirect method has proven to be useful for modeling and predicting forest attribute changes (Esteban et al., 2019; McRoberts et al., 2015a; Økseter et al., 2015; Zhao et al., 2018). This method requires fitting a model for predicting the target variable each time (Bollandsås et al., 2013). However, the high costs of repeated ALS acquisitions restrict their use in forest attribute changes assessment. Using DAP data from regular national and regional aerial surveys may reduce costs associated with remote sensing-derived auxiliary variables acquisitions. Goodbody et al. (2017)

demonstrated that DAP data from unmanned aerial vehicle may be used to estimate changes in V by updating ALS generated inventories using the indirect method. However, indirect method involves field measuring of forest attributes in all dates, which is not always possible due to economic constraints. Fekety et al. (2015) and Domingo et al. (2019) proved that field inventory costs may be reduced using transferable models. However, transferring models can be a non-trivial task because of differences in point cloud characteristics. The methodology proposed by this study enables to fit transferable V models using stable metrics between different types of datasets. Thus, these models can be used to estimate V changes with the indirect method in a cost-effective way.

3.5 Conclusions

This study used ABA forest inventory methods, different sources of ALS and DAP-derived point clouds and repeated field surveys data to analyze V model transferability. A new variable selection method is presented to use stable metrics which enhanced the transfer capacity of SVR models. Although the predictor variable h_{mean} was the most stable metric between all data sources, a metric related to the canopy density was included in all models to improve V estimation. The results of this study demonstrate that SVR models using stable metrics can be transferred not only to point clouds acquired using the same technology (ALS-ALS and DAP-DAP transferability) but also between both technologies (ALS-DAP transferability) without a significant loss of accuracy. This research contributes to more global and transferable models over time, between sensors and between technologies, which may provide an improvement in the efficiency of forest resources monitoring. The proposed methods help to increasing forest data availability and reducing the need of new field sample acquisitions, thus significantly decreasing forest inventory costs.

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Capítulo 4. Integration of UAV, Sentinel-1, and Sentinel-2 Data for Mangrove Plantation Aboveground Biomass Monitoring in Senegal

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Abstract

Due to the increasing importance of mangroves in climate change mitigation projects, more accurate and cost-effective aboveground biomass (AGB) monitoring methods are required. However, field measurements of AGB may be a challenge because of their remote location and the difficulty to walk in these areas. This study is based on the Livelihoods Fund Oceanium project that monitors 10,000 ha of mangrove plantations. In a first step, the possibility of replacing traditional field measurements of sample plots in a young mangrove plantation by a semiautomatic processing of UAV-based photogrammetric point clouds was assessed. In a second step, Sentinel-1 radar and Sentinel-2 optical imagery was used as auxiliary information to estimate AGB and its variance for the entire study area under a model-assisted framework. AGB was measured using UAV imagery in a total of 95 sample plots. UAV plot data was used in combination with non-parametric support vector regression (SVR) models for the estimation of the study area AGB using model-assisted estimators. Purely UAV-based AGB estimates and their associated standard error (SE) were compared with model-assisted estimates using (1) Sentinel-1, (2) Sentinel-2, and (3) a combination of Sentinel-1 and Sentinel-2 data as auxiliary information. The validation of the UAV-based individual tree height and crown diameter measurements showed a root mean square error (RMSE) of 0.21 m and 0.32 m, respectively. Relative efficiency of the three model-assisted scenarios ranged between 1.61 and 2.15. Although all SVR models improved the efficiency of the monitoring over UAV-based estimates, the best results were achieved when a combination of Sentinel-1 and Sentinel-2 data was used. Results indicated that the methodology used in this research can provide accurate and cost-effective estimates of AGB in young mangrove plantations.

Keywords: digital aerial photogrammetry; SAR; model-assisted; biomass estimation; Copernicus; unmanned aerial vehicles

4.1 Introduction

Mangroves are highly productive ecosystems and are able to sequester and store large amounts of carbon (Alongi, 2012; Donato et al., 2011; Murdiyarso et al., 2009). They also play a key role in production of timber and non-timber forest products, shoreline protection, providing fishing areas, or filtering water pollution (Barbier et al., 2011; Murdiyarso et al., 2009). For these reasons, mangrove ecosystems are highly interesting zones for climate mitigation and adaptation projects (Alongi, 2002).

In the last few years, the attention to afforestation and reforestation projects as well conservation programs, such as Reducing Emissions from Deforestation and Forest Degradation Plus (REDD+), has increased. These programs require accurate estimations of biomass and carbon stocks in vegetation and soils to monitor changes in extent, carbon emissions, and sequestration rates. The use of new technologies based in remote sensing can improve the accuracy of monitoring and enhance our understanding of the changes in forested mangrove areas (Lagomasino et al., 2016).

Traditional inventory data collection methods may be accurate and offer detailed information on the composition and structure of forests (Köhl et al., 2006). However, this task can be inefficient or time-consuming (Gardner et al., 2008) in remote or hard-to-reach locations and difficult-to-work areas (i.e., mangroves). Monitoring mangrove forests is also arduous because of their large extent (Feliciano et al., 2017), thus remote sensing data has been widely used for this purpose. The kind of remote sensing platform used depends on the scale and the goal of the research (Surový et al., 2018). Low- and medium-resolution space-borne sensors availability is generally free of charges or cheaper than airborne sensors and they offer larger coverage area while airborne and unmanned aerial vehicles (UAV) sensors have much more spatial resolution but limited autonomy, which can result in a higher cost per hectare. Given that soil is the main carbon pool in this type of forests (Adame and Fry, 2016; Alongi, 2012) most studies have focused on investigating changes in mangrove land cover (Shapiro et al., 2015) since soil carbon is relatively stable (Adame and Fry, 2016).

Many studies have monitored the mangrove forests coverage using space-borne imagery, from low-resolution sensors, such as MODIS (Dutta et al., 2015), or medium-resolution satellite imagery, such as LANDSAT (Giri et al., 2011), to very-high resolution (VHR) imagery from WorldView-2 (Kamal et al., 2014). Recent studies have analyzed the vertical structure of mangrove forests from space-borne and airborne observations. Simard et al. (2006) and Fatoyinbo et al. (2008) used the Shuttle Radar Topography Mission (SRTM) for mangroves canopy height estimation, while Polarimetric Synthetic Aperture Radar Interferometry (Pol-

InSAR) was applied to data collected from the TanDEM-X InSAR (TDX) by Lee and Fatoyinbo (2015); Lee et al. (2015), and Lola Fatoyinbo et al. (2017). VHR satellite stereophotogrammetry has also been used to create canopy height models (CHM) (Lagomasino et al., 2016). On the other hand, the airborne laser scanning (ALS) also provides elevation data to estimate canopy heights and to calibrate and validate estimations from space-borne remote sensing sensors (Feliciano et al., 2017; Lagomasino et al., 2016; Lola Fatoyinbo et al., 2017).

Within the satellite remote sensing techniques, synthetic aperture radar (SAR) sensors can be more effective for monitoring forest biomass since they are independent of cloud conditions (Lu, 2006) and can penetrate the canopy (Laurin et al., 2018; Sinha et al., 2015). SAR sensors use different wavelengths which are able to penetrate the forest in different ways (Laurin et al., 2018). The X- band and C-band are sensitive to leaves and needles (Le Toan et al., 1992). These bands are suitable for monitoring young growth stages of mangrove forests or plantations (Lucas et al., 2017). The launch of Sentinel-1A and Sentinel-1B enables very frequent SAR data acquisitions under a free data policy. Sentinel-1 provides SAR images with a high geometric resolution (5 m × 20 m on the ground) with HH+HV or VV+VH polarizations in the C-band (Torres et al., 2012). Nevertheless, C-band backscatter saturation levels are typically low in mangrove biomass estimations (50–70 Mg ha⁻¹) (Kuenzer et al., 2011; Proisy et al., 2002). Some studies have demonstrated that the integration of SAR and optical sensors data improves forest biomass estimates since optical data contributes to offset the saturation effect (Pham et al., 2018; Vafaei et al., 2018). Thus, the opportunities for mangrove biomass monitoring have improved with the subsequent launch of Sentinel-2 (multispectral) satellites of the European Commission's Copernicus program.

Models relating observations of forest attributes measured on field plots and remotely-sensed data for the same plots are often used when plot-based estimates are not sufficiently precise or there are not enough field plots available (Næsset et al., 2015). Model-based inference is based solely on assumptions of the model (Ståhl et al., 2016). Therefore, under model-based frameworks estimators may be both biased and imprecise depending on the goodness of the model (Ståhl et al., 2016). On the other hand, the use of models in the context of design-based inference does not have this problem and models may be used to enhance the variance (Næsset et al., 2011). In this way, an inadequately specified model using design-based inference through model-assisted estimation will not lead to biased estimators (Ståhl et al., 2016). Model-assisted frameworks have been extensively used in large-area aboveground biomass (AGB) monitoring (Næsset et al., 2015, 2011; Sannier et al., 2014).

Non-parametric models have been widely used for AGB estimation (Güneralp et al., 2014; Pham et al., 2018, 2017; Shao and Zhang, 2016; Vafaei et al., 2018). The use of machine learning algorithms, such as k-Nearest Neighbor (k-NN), back propagation neural networks (BPNN), multilayer perceptron neural network (MLPNN), random forest (RF), or support vector regression (SVR), have been extended due to their ability to model relatively easy complex non-linear relationships between the variables and to process large dataset efficiently (Gleason and Im, 2012). Although parametric models have been more frequently used in connection with model-assisted estimation, non-parametric models have also been employed (Baffetta et al., 2011; Magnussen and Tomppo, 2016).

During the past few years, digital aerial photogrammetry (DAP) has reached great importance in digital surface models (DSM) generation due to the improvements in hardware and photogrammetric algorithms, such as structure-from-motion (SfM) (Gehrke et al., 2008; Remondino et al., 2014). Three-dimensional (3D) ALS-like point clouds may be produced by photogrammetric matching of digital aerial images (Penner et al., 2015; Pitt et al., 2014; White et al., 2013b). However, DAP-based point clouds only provide information at the top surface, therefore, an accurate bare-earth digital terrain model (DTM) for estimating canopy height and structure is essential (Vastaranta et al., 2013). However, DTMs may be produced by photogrammetry without any support from other sensors in open canopy forests (Mohan et al., 2017). Furthermore, recent studies have shown the application of UAVs in forest variables estimation (Dandois and Ellis, 2013; Gini et al., 2012; Lisein, 2012; Panagiotidis et al., 2017; Puliti et al., 2018; Tao et al., 2011). One of the main advantages of DAP-based point clouds generated from UAV imagery is the capacity to detail the vegetation at the centimeter level (Goodbody et al., 2017a). VHR imagery allows for individual tree crown (ITC) extraction from the DAP-derived canopy models (Zarco-Tejada et al., 2014) and for measuring parameters like individual tree height or crown surface. Such measurements are very useful as they are good estimators of other interest variables as, inter alia, diameter at breast height, volume, AGB, or tree growth (Iizuka et al., 2017; Panagiotidis et al., 2017). Thus, these facts coupled with the low operational cost of UAVs (Anderson and Gaston, 2013) has resulted in UAVs being used as a popular alternative in ecosystems for surveying and mapping (Mweresa et al., 2017).

Particularly, only a few studies have researched the application of UAVs to the mangrove ecosystems (Cao et al., 2018; Otero et al., 2018; Tian et al., 2017). Nevertheless, UAVs may be a practical solution in remote areas since they allow us to develop rapid and cost-effective surveying forest attributes (Dandois and Ellis, 2013)(Dandois and Ellis, 2013; Mlambo et al., 2017; Otero et al., 2018; Puliti et al., 2015). Using UAVs also provides an advantage over other remote sensing systems due to the possibility to plan imagery capture during low

sea tide. Although digital photogrammetry from UAVs leads to good estimations of mangrove forests parameters, it is costly for wall-to-wall large-scale forest inventories. Instead, UAVs may be used in assessing tree variables at the plot-scale. To our knowledge, only Mayr et al. (2017) have researched the use of photogrammetric point clouds from UAVs to delineate tree crowns in separate plots.

This study purposes a novel technique to quantify AGB in large areas of young reforested mangroves replacing traditional field sampling methods by photogrammetric point cloud-based measurements and using wall-to-wall Sentinel-1 and Sentinel-2 data as auxiliary information. The aims of this study were (1) to evaluate the performance of low-cost UAV-derived photogrammetric point clouds for the measurement of individual tree heights and crown diameters, (2) to investigate the usability of wall-to-wall Sentinel-1 and Sentinel-2 data as auxiliary information for estimating the AGB using a probability sampling design, and (3) to compare the AGB estimates and their precisions for the different satellite data.

4.2 Material and Methods

4.2.1 Study area

This study was conducted in the mangrove forest of Senegal in the Sine Saloum and Casamance Deltas (12°20'–14°10' N; 15°24'–16°47' W) located in the west coast of the country (Figure 4.1). The study area is located in a mangrove restoration project with a total area of 10,415.12 ha that was planted between 2009 and 2012 (1550.05 in 2009; 4285.14 in 2010; 3337.47 in 2011 and 1242.46 in 2012). The project area consists of 2657 planted parcels, scattered in the deltas, with a mean area of 3.92 ha. The species planted is *Rhizophora mangle* L. with a mean planting density of 5000 trees/ha (Agresta S. Coop., 2014).

The Sine Saloum delta is in the Sudanese climate domain with annual precipitation ranging from 450–920 mm, while the parcels located in the Casamance area are in the Sudanese-Guinean and sub-Guinean climate domains where annual precipitation ranges between 800–1700 mm (Andrieu, 2008). Average air temperature ranges from 26 °C to 29.7 °C in the Casamance area and between 27.2 °C and 30 °C in the case of Sine Saloum (Deugué-Namboma, 2008). The monsoonal rainy season is a result of the St. Helen High and lasts from June to September (Guèye et al., 2012).

Figure 4.1 Overview of the study area on the west coast of Senegal, stratification, and sampling design.

4.2.2 Satellite Data. Acquisition, and Preprocessing

Sentinel-1 dual-polarized images in Interferometric Wide Swath (IW, 250 km swath width) and Sentinel-2 images were acquired, from the European Space Agency (ESA) Sentinel science hub (<https://scihub.copernicus.eu/>) (Table 4.1), to provide AGB estimations. Additionally, Sentinel-2 data was used to stratify the study area.

Table 4.1 Remotely-sensed data acquisition.

Sensor	Application	Acquisition Period	Processing Levels	Bands
S2	Stratification	February 2017	Level-1C	B2, B3, B4, B5, B6, B7, B8A, B9, B11, B12
		March 2017 (7 scenes)		
	AGB prediction	July 2017 August 2017 (6 scenes)		
S1	AGB prediction	July 2017 September 2017 (6 scenes)	Level-1 GRD	C-band (VH polarization)

S2 = Sentinel-2; S1 = Sentinel-1; GRD = ground-range detected.

The study area region is covered by two Sentinel-1 scenes and for each one, three Standard Level 1 Products GRD (ground-range detected) were acquired in ascending mode in the same period of time within which the UAV-based inventory was carried out and considering the sea tide level at the satellite acquisition time over the study area. Sentinel-1 products processing workflow consisted of four steps achieved in SNAP 6.0 software (Zuhlke et al., 2015): (i) radiometric calibration (output was sigma0 band), (ii) terrain-correction, based on SRTM digital elevation model (three-second resolution), (iii) single-product speckle filtering based on a three pixel size Lee filter, and (iv) a linear conversion to dB. The outputs were backscatter images at 20 m resolution. In this study, only VH polarization images were included in the modeling scheme since it has been shown to be more efficient than VV and HH for the AGB estimation because it is less influenced by soil moisture (Huang et al., 2018). The three-date data were averaged to generate a mean VH polarization image.

Table 4.2 Sentinel-2 imagery data bands and vegetation indices used in this study.

Predictor Variable	Band/Index	Definition
Multispectral bands	B2	Blue, 490 nm
	B3	Green, 560 nm
	B4	Red, 665 nm
	B5	Red edge, 705 nm
	B6	Red edge, 749 nm
	B7	Red edge, 783 nm
	B8	Near Infrared (NIR), 842 nm
	B8A	Near Infrared (NIR), 865 nm
	B9	Water vapor, 945 nm
	B11	Short-wavelength infrared (SWIR-1), 1610 nm
	B12	Short-wavelength infrared (SWIR-2), 2190 nm
Vegetation indices	NDVI1	$(B8 - B4)/(B8 + B4)$
	NDVI2	$(B8A - B4)/(B8A + B4)$
	NDI45	$(B5 - B4)/(B5 + B4)$,
	SAVI	$(B8 - B4)/(B8 + B4 + L) * (1.0 + L)$ L = 0.5
	TCARI	$3 * [(B5 - B4) - 0.2 * (B5 - B3) * (B5/B4)]$
	OSAVI	$(1.16) * (B8 - B4)/(B8 + B4 + 0.16)$
	MCARI	$[(B5 - B4) - 0.2 (B5 - B3)] * (B5/B4)$
	GNDVI	$(B8 - B3)/(B8 + B3)$
	PSSRa	B8/B4
	IRECI	$(B8 - B4)/(B5/B6)$

NDVI = Normalized Difference Vegetation Index; SAVI = Soil Adjusted Vegetation Index; TCARI = Transformed Chlorophyll Absorption Ratio Index; OSAVI = Optimized Soil Adjusted Vegetation Index;

MCARI = Modified Chlorophyll Absorption in Reflectance Index; GNDVI = Green Normalized Difference Vegetation Index; PSSRa = Simple Ratio 800/680 Pigment Specific Simple Ratio (Chlorophyll a); IRECI = Inverted Red-Edge Chlorophyll Index.

For our study purposes, we used the spectral bands with 10 m and 20 m resolutions, while bands at 60 m were excluded from the analysis. The Sentinel-2A Level 1-C Top-of-Atmosphere (TOA) reflectance images were processed to Level-2A bottom-of-atmosphere (BOA) values using the freely available SNAP toolbox (Zühlke et al., 2015) and the associated Sen2Cor plug-in (Müller-Wilm, 2016). Sentinel-2 bands were resampled to match the 20 m spatial resolution of the Sentinel-1 VH polarized backscatter. Ten different vegetation indices were generated from multispectral Sentinel-2 data (Table 4.2).

For all survey plots, bands, vegetation indices from the Sentinel-2 Level 2-A and backscatter mean values from the Sentinel-1 products were computed using the *Extract* function in the *Raster* package (Hijmans and van Etten, 2016) within the R software environment (R Core team, 2015).

A flowchart showing the general research framework for estimating the AGB of mangrove plantations used in this study is presented in Figure 4.2.

Figure 4.2 General methodology workflow used for AGB estimation integrating the Sentinel SAR and multispectral data. UAV-derived imagery was used for sampling plot measuring.

4.2.3 Stratification and Sampling Design

A total of seven Sentinel-2 images were initially used as auxiliary information to generate a wall-to-wall stratification of the mangrove plantations in the study area, which aids to encompass the full range of available AGB. Two main strata were defined to allocate

efficiently a stratified systematic sample of UAV-based plots in each of them, (i) one with very low AGB densities due to high plantation mortality and low plantation development stage (Stratum I) and (ii) the second stratum with higher AGB densities and therefore, lower mortality rates and higher tree cover and plantation development stage (Stratum II).

The random forest (RF) classifier (Breiman, 2001) was selected to perform the stratification classification and it was implemented using the R-Package *Random Forest: Breiman and Cutler's Random Forests for classification and regression* (Liaw and Wiener, 2002). Random forests improve classification accuracy by growing an ensemble of classification trees and letting them vote on the classification decision. For the model training, regions of interest (ROIs) of the two strata were manually defined based on field information and observations of canopy cover over high resolution images from Google Earth.

Two RF models were fitted, one for the classification of 9th March 2017 (western zone of the study area) images and one for classifying 24 February 2017 images (eastern zone). A total of 20 variables were used as predictors in the image classification procedure: 10 Sentinel-2 spectral bands and 10 Sentinel-2 vegetation indices (Table 4.2). A random forest variable selection algorithm VSURF (Genuer et al., 2015) was applied to reduce the number of predictor variables and to improve the performance of the Random Forest models (Table 4.3).

Table 4.3 Predictor variables from Sentinel-2 imagery data used in random forest classification and variables finally selected by VSURF.

Images Date	RF Predictor Variables	VSURF Selected Variables
9 March 2017	B2, B3, B4, B5, B6, B7, B8, B8A, B9, B12, NDVI1, NDVI2, NDI45, SAVI, TCARI, OSAVI, MCARI, GNDVI, PSSRa, IRECI	B3, B12, OSAVI, NDVI2, NDI45, B9, B8
24 February 2017	B2, B3, B4, B5, B6, B7, B8, B8A, B9, B12, NDVI1, NDVI2, NDI45, SAVI, TCARI, OSAVI, MCARI, GNDVI, PSSRa, IRECI	NDVI2, B3, B9, B12

The areas of the two strata in the study region were 6927.03 ha for Stratum I and 3488.09 ha for Stratum II. A stratified systematic sample of UAV-based plots was designed for the two pre-defined strata. The sample size was adapted to suit the time available to carry out the inventory, so the sample consisted of 95 circular plots with a radius of 10 m and an area of 314.16 m² plots. The dataset was randomly divided into 60% training and 40% validation data samples (57 and 38 sample plots respectively). Based on a target of equal allocation of n_h = 50 plots per stratum, the systematic sample was distributed on a grid of 1200 m by 1200 m and 850 by 850 m in Stratum I and II, respectively. The spacing of the grid was determined as:

$$l_h = \sqrt{\frac{A_h}{n_h}}, \quad (4.1)$$

where l_h is the spacing of the grid for the stratum h , A_h is the size of the stratum h (m²), and n_h is the initial number of sample plots for the stratum h .

4.2.4 Sampling Data Collection and Processing

Aerial and field measurement campaigns were done simultaneously during the months of July and August 2017 in low tide conditions. UAV imagery was acquired in 95 flights (i.e., one per sample plot) using a commercial compact Parrot Bebop 2 quadricopter (Parrot SA, Paris, France). Pix4dCapture software (Pix4D SA, Lausanne, Switzerland) was used to design and guide each mission flight. In order to achieve a better 3-D representation of the plots, a circular mission option was chosen since it is recommended for small areas and 3D model outputs (e.g., point clouds) at an altitude of 25 m above ground. This kind of mission ensures that the images are taken from all angles around a point of interest with the required overlap for photogrammetric processing (Pix4D, 2018a). The oblique imagery provides a more detailed characterization of the sample trees (Cunliffe et al., 2016).

Tree height and crown diameters were measured in the field on 100 different trees (between one and three trees per plot) to compare and validate field and UAV-based measurements. Before each UAV flight, colored disks were placed next to the measured trees to locate them in the point clouds. Tree heights and crown diameters measured over the photogrammetric point cloud were added to the trees database.

Each of the 95 flights was processed separately for DAP point clouds and orthomosaics generation using the photogrammetry software Pix4Dmapper (Pix4D SA, Lausanne, Switzerland) (Pix4D, 2015). Pix4Dmapper uses proprietary algorithms based on computer vision structure-from-motion (SfM) and stereo-matching algorithms to align images and build a georeferenced sparse point cloud. For images taken with the Bebop 2 drone, the sky is automatically removed in the image alignment phase in Pix4D. After this step the point cloud is densified using multi-view stereo-reconstruction algorithms. For this study, a half size image scale was used for the point clouds densification as it is recommended by the software developers (Pix4D, 2018b). As no additional ground control points (GCP) were collected for enhancing accuracy, only the GPS coordinates of the tagged images were used in this process. Hence, coordinates of sample plots were determined by the UAV GPS/INS system and the photogrammetric reconstruction.

Bare-earth was extracted from the point clouds and the height above the ground was computed for each point using the *Lasground* tool in Lastools (Isenburg, 2014). The algorithm parameters were also fine-tuned for an optimum result (step was 2 m, bulge was 1 m, spike was 0.01 m and standard deviation was 10 m). The point clouds were clipped to the spatial extent of the sample plots (i.e., circular with a radius of 10 m). Ground points were used to generate gridded DTMs with a resolution of 0.5 × 0.5 m and the vegetated above ground points were used to create 0.1 m DSMs. After this, a 0.1 m resolution CHM was generated for each sample plot by subtracting bare earth heights from the DSM heights. FUSION software (Mcgaughey and Carson, 2003) was used for DTM and CHM creation.

Heights and positions of individual trees inside the plot were determined using local maxima filters based on a locally-variable window size (Kini and Popescu, 2004; Popescu et al., 2002; Popescu and Wynne, 2004). This algorithm identifies the highest point within a variable window. For this, the filter moves the window over the CHM and uses a circular window to determine if the center pixel is a local maximum by comparing this pixel with the surroundings pixels within the window. Window size depends on tree height by referring to a predefined height- crown equation. In order to achieve the best results and taking in account that tree sizes are different in each plot, various windows sizes were tested using the *CanopyMaxima* function of FUSION. Afterwards, a manual debug of the results was carried out using the orthomosaics derived from UAV data as reference to ensure the measurement of all trees in plots. Finally, tree crown surfaces were delineated computing the *rLidar* package (Silva et al., 2017) within the R software environment (R Core team, 2015). The tree crown diameter was calculated as the diameter of the circle with equivalent area:

$$cd = \sqrt{\frac{4CC_{UAV}}{\pi}}, \quad (4.2)$$

where cd is the tree crown diameter (cm) and CC_{UAV} is the tree crown area.

Only trees with 50% of their crown surface within the plots were considered in sampling. An exhaustive manual revision of the detected trees was done to avoid committing omission and commission errors. In order to ensure the quality of UAV-based measurements, all plots were reviewed by a different expert than the one who carried out the semiautomatic process of the sample plot measuring.

4.2.5 Allometric Equation

The *agb* for individual trees was estimated using an allometric equation developed specifically for the project (Table 4.4) (Agresta S. Coop., 2017). A specific equation was developed for *Rhizophora* based on a destructive sample of 71 trees from the study area. The *agb* was defined as the sum of stem, stilt roots, branches, leaves, and fruits biomass. The *agb* allometric equation adjusted in the project has considered two independent variables (tree crown diameter and total height). These variables were the necessary ones for the estimation of tree AGB based on the photogrammetric information. The point clouds obtained during the UAV-based sampling of this study provided information of crown diameter and tree height at the individual tree-level. Based on the single-tree estimates of AGB, this attribute was computed for each field plot (Table 4.5).

Table 4.4 Tree allometric equation used for aboveground biomass estimates.

Equation	R^2	Number of Individuals	CD Range (cm)	h Range (cm)
$agb = 0.004932696 \times cd^{1.9869} \times h^{0.7166}$	0.93	71	10.5–210.0	37–285

Table 4.5 Summary of AGB results for the 95 UAV-based sample plots ($Mg\ ha^{-1}$).

Stratum	Number of Plots	Minimum	Mean	Maximum	Standard. Deviation
I	55	0.00	0.33	1.60	0.49
II	42	0.00	8.05	36.93	9.72

4.2.6 Aboveground Biomass Modelling and Performance Assessment

Remote sensing data from Sentinel-1 and Sentinel-2 were used to enhance estimators of AGB predictions under the model-assisted inferential framework since this study was designed according to design-based principles. This method requires of models that relate AGB to the variables extracted from satellite data.

In the current study, SVR was used to estimate machine-learning models of the mean function. SVR has been used with good results in other remote sensing derived biomass estimations including mangrove plantations (Englhart et al., 2012; Jachowski et al., 2013; Pham et al., 2018; Shao and Zhang, 2016; Vafaei et al., 2018). The SVR basis is to transform the multidimensional regression problem into a linear one to predict one-dimensional variables. This problem is solved by using appropriate kernel functions to map the training data into a new hyperspace feature (Smola and Schölkopf, 2004). In this study, the radial

basis function (RBF) kernel was used due to its wide usage in other studies for modelling forest AGB (López-Serrano et al., 2016; Pham et al., 2018; Vafaei et al., 2018). The Vapnik's ϵ -insensitive loss function (Vapnik, 1995) was used to reduce model complexity by ignoring differences between predicted and true values smaller than ϵ . In order to minimize problems due to overfitting and achieve parsimonious models the best kernel-parameter combination of ϵ , the regularization parameter (C) and the kernel width (γ) was selected using the grid search method. During this step a 10-fold cross-validation was performed to assess the accuracy of the models.

To improve the accurateness of the models a backwards selection of predictors based on the predictor importance ranking was used by applying the recursive feature elimination (RFE) and relative variable importance algorithms in R (caret package) (Kuhn et al., 2014). The relative variable importance was also assessed using the same R-package.

Three different models were adjusted; one per each data source and another one by combining both satellite datasets. A selection of predictive variables was applied in a first step except for the Sentinel-1 model. In order to assess the goodness-of-fit of the models, predictions were compared to the validation dataset using a variety of metrics: absolute (RMSE), mean absolute error (MAE) and coefficient of determination (R^2):

$$RMSE = \sqrt{\frac{\sum_1^n (\hat{y}_i - y_i)^2}{n}}, \quad (4.3)$$

$$MAE = \frac{1}{n} \sum_1^n |\hat{y}_i - y_i|, \quad (4.4)$$

$$R^2 = 1 - \frac{\sum_1^n (y_i - \hat{y}_i)^2}{\sum_1^n (y_i - \bar{y})^2}, \quad (4.5)$$

where n is the total number of validation plots; y_i is the observed AGB value plot i ; $\hat{y}_i$ is the predicted AGB value for plot i , and $\bar{y}$ is the mean of observed AGB values for all validation sample plots.

Akaike information criterion (AIC) was used to compare the performance of the different models. AIC has been recently used for comparing models in other studies that have estimated AGB based on remotely-sensed data (Pham et al., 2017; Vaglio Laurin et al., 2014).

4.2.7 Aboveground Biomass Estimation Methods

The fitted SVR regression models were used to estimate AGB of the entire area by a model-assisted procedure. The design used allowed to estimate AGB on the basis of stratum and region-specific information. The plantation area was tessellated into grid cells using regular grids with the same area as backscatter image raster (400 m²). Utilizing the nomenclature proposed by Särndal et al. (1992) used in Næsset et al. (2011) for a stratified random sampling (STRS), the entire population of grid cells in the study area is named U , where $U = \{1, \dots, N\}$. Let U be partitioned into H non-overlapping strata, U_h . In this case $H = 2$. Let N_h denote the size of U_h with $h = 1, \dots, H$. Let b_k be the AGB of the k :th unit in the population.

The following estimator was used to estimate the mean AGB from the purely UAV-based sampling for each stratum:

$$\hat{B}_{STRSh} = \frac{\sum_{k \in s_h} b_k}{n_h}, \quad (4.6)$$

where s_h is a sample of fixed size n_h randomly designed.

The mean AGB for a particular stratum may be estimated using the model-assisted regression estimator (MAR) described in (Næsset et al., 2015) as follows:

$$\hat{B}_{MARh} = \frac{\sum_{k \in U_h} \hat{b}_k}{N_h} + \frac{\sum_{k \in s_h} \hat{e}_k}{n_h}, \quad (4.7)$$

where $\hat{b}_k$ is predicted AGB for the k :th grid cell, N_h is the total number of grid cells for the stratum h , and $\hat{e}_k = b_k - \hat{b}_k$. The first term of Equation (4.7) is the synthetic regression estimator described in Särndal et al. (1992). This estimator is a sum of model estimates of each element in the population.

On the other hand, the second term is a Horvitz-Thompson estimator of the *bias* between the model predictions and the observed values in the sample for the stratum h . The Horvitz-Thompson estimator functions as a correction factor that makes the MAR asymptotically unbiased when n_h is not too small (Särndal et al., 1992).

The following estimator of the variance of the mean AGB estimation from the UAV-based alone was used:

$$\hat{V}(\hat{B}_{STRSh}) = \frac{\sum_{k \in S_h} (b_k - \hat{B}_{STRSh})^2}{n_h(n_h - 1)} \quad (4.8)$$

The variance of the mean AGB for the MAR was estimated as follows:

$$\hat{V}(\hat{B}_{MARh}) = \frac{\sum_{k \in S_h} \left(\hat{e}_k - \frac{\sum_{k \in S_h} \hat{e}_k}{n_h} \right)^2}{n_h(n_h - 1)} \quad (4.9)$$

The stratified estimator was used to estimate mean AGB for the entire study area. Equation (4.10) is the stratified estimator of AGB for the UAV-based sample and Equation (4.11) is the stratified estimator of mean AGB for the MAR:

$$\hat{B}_{STRS} = \sum_h \frac{N_h}{N} \hat{B}_{STRSh} \quad (4.10)$$

$$\hat{B}_{MAR} = \sum_h \frac{N_h}{N} \hat{B}_{MARh} \quad (4.11)$$

Finally, the following variance estimators for the entire study area were used:

$$\hat{V}(\hat{B}_{STRS}) = \sum_h \left(\frac{N_h}{N} \right)^2 \hat{V}(\hat{B}_{STRSh}) \quad (4.12)$$

$$\hat{V}(\hat{B}_{MAR}) = \sum_h \left(\frac{N_h}{N} \right)^2 \hat{V}(\hat{B}_{MARh}) \quad (4.13)$$

The standard errors (SE) were calculated for each stratum as the square root of the estimator of the variance of the mean AGB based on UAV-based and model-assisted methods, respectively. The relative efficiency (RE) parameter was computed for each model-assisted to compare UAV-based sample precision with the different model-assisted precision as follows:

$$RE = \frac{\hat{V}(\hat{B}_{STRS})}{\hat{V}(\hat{B}_{MAR})} \quad (4.14)$$

where RE is the relative efficiency of different model-assisted over purely UAV-based sample. The greater than 1.0 is RE the higher is the efficiency of model-assisted estimates than UAV-

based and the larger is the UAV-based sample size required to achieve the same results as the model-assisted method.

4.3 Results

4.3.1 Tree Measurements

Figure 4.3 shows the results of location and measurement of individual trees from the semiautomatic processing of the photogrammetric point clouds manually revised.

Figure 4.3 Example of individual tree detection from UAV-derived CHM, local maxima (m), and crown delineation for a sample plot.

The correlation coefficient between field-measured heights and UAV-measured heights was significant with a value of 0.95 (intercept of 6.1 cm and slope of 1.07) (Figure 4.4a). Paired *t*-test showed that both measures are significantly different. The mean difference between field height and the UAV height was 11.59 cm (95% confidence interval from 7.99 cm to 15.19 cm). UAV point cloud measurements tended to underestimate the tree heights (Table 4.6). The root mean square error (RMSE) for individual tree heights was 0.21 m.

Figure 4.4 Scatter plot detailing the coefficient of determination (R^2) between (a) field measured height (m) and the maximum height from UAV-derived point clouds for individual trees and (b) field measured tree crown diameters (m) and tree crown diameters from UAV-derived point clouds. The red line shows the linear fit of the UAV-derived point clouds measurements and field observed values. The grey line in the center indicates 1:1.

Table 4.6 Summary of the measured and estimated tree variables (m).

	Field Tree Height	UAV Tree Height	Field Tree Crown Diameter	UAV Tree Crown Diameter
Minimum	0.35	0.23	0.08	0.01
Mean	1.12	1.00	0.85	0.81
Maximum	3.40	2.89	3.03	2.67

Figure 4.4b shows the strong linear relationship between the point cloud-derived and field measured tree crown diameters ($R^2 = 0.75$). As in the case of tree height, tree crown diameters were slightly underestimated with a *bias* of 3.17 cm (95% confidence interval from -3.47 cm to 9.81 cm). The two-sided *t*-test revealed that there were no significant differences ($p \geq 0.95$) between the mean of the crown diameters measured over the point clouds and reference values. The RMSE of tree crown measurements was 0.32 m.

4.3.2 Model Fitting

AGB in the 95 UAV-measured plots was regressed against the predictor variables computed from Sentinel-1 and Sentinel-2 data using SVR. Table 4.7 shows the performance for the validation dataset of the different SVR models generated using Sentinel-1, Sentinel-2 and the combination of both datasets to estimate the mangrove plantations AGB (Mg ha⁻¹). The selected SVR models explained 71–90% of the variability. AGB modelling results showed higher accuracy using SAR data than using optical data alone or in combination with SAR

data. The SVR models for AGB contained a maximum of five explanatory variables (Table 4.7) with Sentinel-2-derived vegetation indices being more important than spectral bands. SAR-based model achieved the highest R^2 and the smallest $RMSE$ and MAE values, while the model based only on spectral indices showed the worst results. The combination of both satellite datasets did not improve the $RMSE$ and MAE as the results are slightly lower compared to the SAR-based model. Regarding AIC values, the best model for AGB included both SAR and multispectral data. Scatter plots of observed versus predicted AGB in the validation dataset for the different models are displayed in Figure 4.5. Figure 4.6 summarizes the variable importance metrics for AGB model predictors.

Figure 4.5 Scatterplot of observed against predicted values from the cross-validation for the (a) Sentinel-1 SVR model, (b) Sentinel-2 SVR model, and (c) Sentinel-1+Sentinel-2 SVR model. The red line shows the linear fit of the predicted and observed values. The grey line in the center indicates 1:1.

Table 4.7 Performance of the selected SVR models.

Inputs	Selected Variables	R^2	RMSE (Mg ha ⁻¹)	MAE (Mg ha ⁻¹)	AIC
Sentinel-1	VH	0.90	2.22	0.89	89.27
Sentinel-2	PSSRa, NDVI2, GNDVI, IRECI, OSAVI	0.71	3.74	1.91	218.23
Sentinel-1+ Sentinel-2	VH, IRECI, SAVI, OSAVI	0.89	2.35	1.20	67.33

4.3.3 Estimations of Aboveground Biomass

For the entire studied area, the UAV-based estimation produced a mean AGB value of 2.90 Mg ha⁻¹ (SE = 0.55 Mg ha⁻¹) (Table 4.8). Using remotely-sensed auxiliary data under a model-assisted framework the corresponding estimations ranged between 2.51 Mg ha⁻¹ (SE = 0.43 Mg ha⁻¹) to 3.66 (SE = 0.38 Mg ha⁻¹).

Figure 4.6 Variable importance measures generated for an SVR model including all variables.

The combination of SAR and optical data showed the greatest RE. Consequently, combining both spaceborne data resulted in an improvement in an efficiency improvement of 115% compared to the purely UAV-based method.

Table 4.8 Estimated mean AGB ($\hat{B}$) and standard error (SE) estimates (Mg ha^{-1}) based on UAV-based sampling and model-assisted estimation from Sentinel-1, Sentinel-2, and the combination of both satellite data.

Stratum	UAV-Based		Model-Assisted								
	$\hat{B}$	SE	Sentinel-1			Sentinel-2			Sentinel-1 + Sentinel-2		
			$\hat{B}$	SE	RE	$\hat{B}$	SE	RE	$\hat{B}$	SE	RE
I	0.33	0.35	0.99	0.31	1.27	0.75	0.30	1.32	0.95	0.35	0.98
II	8.05	1.50	8.50	0.97	2.37	6.04	1.16	1.68	9.12	0.88	2.87
All	2.90	0.55	3.49	0.38	2.06	2.51	0.43	1.61	3.66	0.38	2.15

The mean model-assisted AGB estimates in the stratum I ranged from 0.75 to 0.99 Mg ha^{-1} ($\text{SE} = 0.30\text{--}0.35 \text{ Mg ha}^{-1}$) while for the UAV-based the mean AGB estimate was 0.33 Mg ha^{-1} ($\text{SE} = 0.35 \text{ Mg ha}^{-1}$). The highest RE was obtained using Sentinel-2-assisted estimates ($\text{RE} = 1.32$). For Stratum II, the estimated mean AGB values ranged between 6.04 and 9.12 ($\text{SE} = 0.88\text{--}1.16 \text{ Mg ha}^{-1}$). The best results in terms of RE were achieved using the combination of spectral indices from Sentinel-2 and the backscatter from Sentinel-1 ($\text{RE} = 2.87$). Figure 4.7 shows the estimated AGB maps generated using the three adjusted SVR models. All maps showed similar patterns of AGB density distribution, but the model based on Sentinel-2 data variables led to lower AGB estimated values than the models including Sentinel-1 VH polarization.

Figure 4.7 Study area AGB maps derived from the three SVR models used in this research. The upper row shows a general view of the AGB estimations while the lower row shows details at a smaller scale.

4.4 Discussion

This study described a new method for large-scale forest AGB monitoring in remote and difficult-to-work areas by combining the use of UAVs for aerial plot measurements and data from Sentinel-1 and Sentinel-2 as auxiliary information. This methodology was used to assist in the development of monitoring of large-scale carbon sequestration projects on multiple plots. In the last few years, CHMs derived from UAV imagery have been extensively used to determine tree locations for various purposes, such as measuring tree height and crown sizes, estimating diameter at breast height, and assessing AGB (Birdal et al., 2017; Iizuka et al., 2017; Mohan et al., 2017; Otero et al., 2018; Panagiotidis et al., 2017). In this case, however, an affordable UAV has been used to generate a specific CHM for each sample plot to measure AGB of plots. Sentinel imagery was used as auxiliary data to estimate AGB in the different strata and the entire study area in a model-assisted framework, as in (Næsset et al., 2011), since the estimators are approximately design-unbiased (Ståhl et al., 2016).

Although high tide can make the generation of a quality DAP-derived DTM difficult or even impossible, all flights were planned to avoid this condition. In addition, flat terrain and open canopies helped with the DTM generation, as in (Guerra-Hernández et al., 2016; Jensen and Mathews, 2016). Successful CHMs were built in every aerial plot. ITC delineation algorithms used in the sample plot measurement led to a more efficient, accurate, and productive job. Sample plots were always placed at the central zone of each point cloud which had the highest overlaps.

The accuracy of tree height measures was lower than in previous studies (Iizuka et al., 2017; Lisein et al., 2013; Panagiotidis et al., 2017). This fact can be due to the significantly lower height that present those trees in comparison with previous studies. However, *RMSE* (20.64 cm) is considered relatively small, so results on measurements of tree heights were satisfactory. UAV-based tree height measures were negative-biased, meaning that this parameter was underestimated in agreement with other surveys (Lisein, 2012; Mayr et al., 2017; Torres-Sánchez et al., 2015). The comparison between UAV and ground measurements showed that it is possible to make conservative and realistic measures of tree heights from the photogrammetric 3D models. The findings from our study demonstrated that UAV-derived point clouds may be successfully used to estimate tree heights and crown diameters in recently established mangrove reforestations. From this information, we can accurately estimate AGB if accurate allometric equations based on tree height or crown dimensions are available. For this study, conservative values of AGB were estimated for each sample plot resulting from the negative biased estimations of individual tree heights. A conservative approach in the estimation of AGB is recommended by the different forest carbon

standards to avoid overestimation of GHG removals. A potential weakness of the methodology followed in assessing the sample plot AGB by measuring tree variables over UAV-derived point clouds is the lack of accuracy of ITC algorithm with increasing density of stands (Gong et al., 2002; Mohan et al., 2017). Tree crown diameter measurements may be inaccurate in mature forests due to irregular shapes of crowns (Mohan et al., 2017). In addition, this method may not be suitable in forests with heterogeneous structure since only the upper canopy is detected (Otero et al., 2018).

While accuracy of UAV-based tree variables measurement was studied using a 100-tree validation sample, the accuracy of plot level AGB estimations was not investigated. Sample plot AGB prediction uncertainty may be assessed using a Monte Carlo bootstrapping approach (McRoberts and Westfall, 2014). We recommend that future research focus on assessing UAV-based AGB estimation uncertainty at the plot level in order to evaluate all potential sources of error.

The second phase of this study was to generate precise estimations of AGB for the whole study area combining the stratified systematic sample of UAV-based plots and full-coverage moderate resolution SAR and optical satellite data. As expected, the models fitted using SAR auxiliary data were able to explain more variability ($R^2 = 0.89\text{--}0.90$) and had lower RMSE values ($RMSE = 2.22\text{--}2.35 \text{ Mg ha}^{-1}$) than the model based only on optical imagery ($R^2 = 0.71$, $RMSE = 3.74 \text{ Mg ha}^{-1}$). These results are satisfactory compared to previous studies on the integration of SAR and optical data for AGB estimation. Aslan et al. (2016) estimated AGB of the coastal wetland vegetation in Indonesian Papua by fusing Landsat-8 OLI and ALOS-2 PALSAR-2 data with $R^2 = 0.46$. Pham et al. (2018) reported a R^2 value of 0.60 in a mangrove plantation on the northern coast of Vietnam. They used SVR models with Sentinel-2 and ALOS-2 PALSAR-2 data. Jachowski et al. (2013) used very high resolution GeoEye-1 and ASTER GDEM V2 elevation data (resolution of 30 m) in mangroves of Southwest Thailand with $R^2 = 0.66$. Higher goodness of fit found in this study may be due to low AGB density in the plantation area compared to the rest of studies which were developed in mangrove forests with denser biomass.

Results showed that VH backscatter was the most important variable for modelling AGB in the study area. This result was consistent with the findings of Alan et al. (2017) and Pham et al. (2018). Although VH polarization showed the best performance estimating AGB in the study area, not using other C-band polarization was the main limitation. Other studies found strong correlation between VV, HH, HV, VV/HH, HH/HV, or VV/HV and AGB (Castillo et al., 2017; Pham et al., 2018; Shao and Zhang, 2016). The other main limitation could be the saturation of C-band in high biomass areas. While C-band is not sensitive to values of AGB

exceeding 50–70 Mg ha⁻¹, the saturation level of the AGB estimation in mangrove forests using L-band has been detected at 100–150 Mg ha⁻¹ (Hamdan et al., 2014; Lucas et al., 2017, 2010; Pham et al., 2018; Proisy et al., 2002). Nevertheless, sample plot AGB in our study area ranged from 0 to 36.93 Mg ha⁻¹ and the C-band is favored for these low biomass areas, i.e., forest regeneration or young plantations (Sinha et al., 2015). Moreover, Prior studies using machine learning methods and L-band showed overestimations of AGB in mangrove plantations at values bellow 50 Mg ha⁻¹ (Pham et al., 2018, 2017). This study showed that VH polarization from Sentinel-1 may be used to correctly estimate AGB in mangrove plantations bellow 30 Mg ha⁻¹ using machine learning algorithms, such as support vector machine.

A model combining Sentinel-1 and Sentinel-2 was adjusted to enhance the sensitivity of C-band backscatter at high AGB levels in mangroves (i.e., areas with pre-existing trees). Although this model resulted in a decrease of accuracy for the very low AGB densities stratum, the findings showed that it was more sensitive to higher AGB levels. No saturation issues were found in the study area for Sentinel-1 data since sample plot AGB values were bellow typical saturation levels for mangrove areas. In this sense, more research is needed to analyze whether Sentinel-2 multispectral data is able to minimize the saturation problem in denser AGB level sites, such as natural mangrove forests or older plantations.

Indices using NIR spectrum (B8 and B8A) and red edge bands were the most important variables among optical data for predicting AGB (Figure 4.6). This is consistent with the findings of Sibanda et al. (2015). None of the individual bands were included in the models. Unlikely our results, NIR bands had the most important role rather than vegetation indices in previous studies (Jachowski et al., 2013; Pham et al., 2018). However, (Castillo et al., 2017) found the highest correlation values for spectral indices, such as IRECI, for modelling AGB in mangrove forests.

The findings of this study have shown that incorporating Sentinel data in a young mangrove plantation monitoring may enhance AGB estimations and achieve more accurate results compared to those obtained by a UAV-based only inventory. Combining data from the stratified systematic sampling and a model based on data from the Sentinel constellation reduced, in all cases, the SE values except for Stratum I model-assisted estimation of AGB for the low-density biomass stratum using auxiliary data from both satellites produced the greatest SE value (SE = 0.35 Mg ha⁻¹). However, this model was the most sensitive to higher biomass densities. The best RE values were achieved in Stratum II using the combination of both satellite data. For this stratum and model, 187% more plots would be needed to obtain the same accuracy by a purely UAV-based inventory under simple random sampling. In this way, a hybrid approach might be recommended, i.e., using Sentinel-1 variables as auxiliary

data for the very low density stands (plantation areas in the first years of establishment) and a combination of SAR and multispectral data for older stands or areas with pre-existing trees.

A correction of the *bias* was used in this study by a Horvitz-Thompson estimator under the model-assisted framework. This conferred an advantage on the estimation of AGB as compared to purely model-based inference because mean and total unbiased estimators are not model accuracy dependent, as the model is only improving the design-based estimator (Särndal et al., 1992; Ståhl et al., 2016).

The results of our study have demonstrated that Sentinel-1 and Sentinel-2 data may be used to develop accurate, rapid, up-to-date estimates of AGB of young mangrove plantations in large areas. The European Commission has adopted a free, full, and open data policy for all Copernicus data, so Sentinel products may be used as cost-effective data to reduce the number of sample plots and improve the results of afforestation, reforestation, and/or revegetation mangrove plantation monitoring. The use of multi-source remote sensing data helped in the stratification phase and led to better results in the modelling and estimation phases. In addition, using UAVs made sample plot measuring easier, reduced costs of inventory, and made it possible to work in the most remote areas. However, the promising results reported in this research must be tested in older plantations and natural forests where saturation issues are expected and denser canopy cover makes ITC delineation more difficult.

4.5 Conclusions

The main innovation of this study was the development of a novel approach to large-scale monitoring of young mangrove forests that combine spaceborne optical and radar data. This approach has enhanced traditional field plot measurements with semiautomatic measures using low-cost UAV-derived photogrammetric point clouds. The assessment of accuracy showed that individual tree variables were successfully measured and confirmed that the followed workflow may be an alternative for quickly gathering precise measurements from sampling plots in remote areas.

This study has also confirmed the good performance of SVR modelling AGB in mangrove plantations. Although the Sentinel-1-based SVR model had the best results in terms of R^2 , RMSE, and MAE, the integration of Sentinel-1 and Sentinel-2 data led to achieve more accurate estimations in the higher biomass areas. The study has demonstrated that remote sensing-assisted monitoring substantially improved the precision of AGB estimates compared to pure UAV-based inventory. The integration of radar and optical data

produced the lowest standard errors of the model-assisted estimations, more especially in the higher AGB stratum. Specific studies focusing on the shape and tree size influence on the UAV-derived accuracy measures and the remote sensing-based models are needed to support mangrove AGB monitoring in different conditions depending of country landscapes.

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Capítulo 5. Discusión

Los resultados de los estudios llevados a cabo en esta tesis contribuyen a comprender las posibles utilidades de la DAP dentro del campo de los inventarios forestales. En concreto, este trabajo se ha enfocado en: (1) analizar el desempeño de la DAP en la estimación o actualización de variables dasométricas mediante métodos de masa a partir de imágenes obtenidas por vuelos tripulados y las posibilidades de actualización de inventarios (Capítulos 2 y 3), y (2) desarrollar una nueva metodología basada en la combinación de sensores para la estimación de carbono en plantaciones de manglar, en la que la DAP se usa para la medición de parcelas de muestreo con métodos de árbol individual a partir de imágenes de UAV (Capítulo 4).

En los Capítulos 2 y 3 se utilizaron imágenes aéreas del PNOA para generar nubes de puntos mediante DAP. En el capítulo 2, con el fin de realizar una comparación lo más realista posible entre la DAP y el ALS se utilizaron las imágenes aéreas generadas durante el vuelo ALS del PNOA y no las tomadas específicamente en los vuelos fotogramétricos del PNOA para la generación de ortofotos. De esta forma, ambos datos fueran tomados simultáneamente, evitando que hubiera cambios en la vegetación que pudieran alterar la comparación de ambos productos. Sin embargo, este vuelo no tuvo las mismas características que los vuelos fotogramétricos estándares del PNOA y otras agencias nacionales debido a que el solape entre pasadas fue mayor. En este caso el vuelo tenía un solape longitudinal del 70% y transversal del 60%, cuando normalmente estas campañas se realizan con un solape longitudinal del 60-80% y transversal del 20-40% (Ministry of Infrastructures and Transport, 2019). Aumentar el solape reduce las zonas ocluidas y aumenta la redundancia de información en las imágenes, y por tanto ofrece una mayor probabilidad de correlacionar puntos en ellas (Lemaire, 2008). A pesar de estas mejoras, Bohlin et al. (2012) y Nurminen et al. (2013) encontraron que aumentar el solape tiene efectos mínimos en la mejora de la precisión de las estimaciones mediante ABA. Las conclusiones de estos artículos coinciden con los resultados observados el Capítulo 3 de esta tesis, donde solapes transversales del 40 % se han mostrado suficientes para obtener resultados robustos. Los GSD (0.22-0.35 m) y solapes (60-70%/40-65%) utilizados en ambos estudios están en el rango de otros encontrados en la bibliografía (Bohlin et al., 2012; Kukkonen et al., 2017; Stepper et al., 2017; White et al., 2015).

En esta tesis, la modelización de variables dasométricas a partir de estadísticos extraídos de las nubes de puntos 3D se ha llevado a cabo utilizando algoritmos de machine learning. Este tipo de modelización se ha mostrado superior a la paramétrica en otros trabajos (Domingo et al., 2018; García-Gutiérrez et al., 2015; Gleason and Im, 2012; Jakubowski et al., 2013; Joibary, 2013). En el Capítulo 2, se usó Random Forest para estimar H_0 , G , N y V . Los modelos RF presentan una serie de ventajas frente a otros algoritmos de machine learning;

por ejemplo, pueden manejar grandes bases de datos gracias a la selección de variables implícita en el proceso de construcción de modelos, y son robustos frente al ruido (i.e. valores atípicos) (Breiman, 2001). Sin embargo, la interpretabilidad de estos modelos es limitada cuando se utilizan muchas variables (Pal, 2017). Para simplificar los modelos y ayudar en el diagnóstico y la interpretación de los mismos, se realizó una selección de variables con la que se discriminó el grupo mínimo de variables no redundantes que mantuviera la precisión de las estimaciones. En el Capítulo 3, en cambio, se usaron modelos Support Vector Regression. Si bien en algunos estudios se ha probado que los modelos SVR tienen mayor poder de predicción que otras técnicas paramétricas y no paramétricas (García-Gutiérrez et al., 2015; Gleason and Im, 2012), es necesario seleccionar correctamente las variables predictoras para incrementar la precisión de las estimaciones, eliminando aquellas que aporten ruido o redundancia (Nguyen and de la Torre, 2010). El método de selección de variables utilizado en los modelos SVR del Capítulo 3 fue diferente. En este caso se buscaron modelos fácilmente interpretables cumpliendo: (i) que incluyeran como máximo una variable de cada uno de los tres grandes grupos de estadísticos de estructura de la vegetación (altura, dispersiones de altura y cobertura) y (ii) que las variables seleccionadas fueran estables entre las fuentes de datos utilizadas (ALS y DAP). Esta selección de variables se realizó con el fin de alcanzar un equilibrio entre la capacidad de transferibilidad de los modelos y la de predicción; buscando la máxima precisión en modelos que además fueran transferibles tanto temporalmente dentro de la misma tecnología como entre tecnologías.

Los objetivos perseguidos en los Capítulos 2 y 3 motivaron que la selección de variables se realizara de una manera diferente en cada caso. Por este motivo, los resultados del Capítulo 3 no se han tenido en cuenta en esta tesis en la comparación de precisiones en la estimación de V entre DAP y ALS. Sin embargo, al igual que en el Capítulo 2, los resultados de los modelos estuvieron dentro del rango observado en otros estudios, tanto para ALS como para DAP (Tabla 2.5). Los resultados de la validación cruzada de los modelos RF utilizados para estimar variables dasométricas en un monte de *P. pinaster* muestran que, al igual que en el caso del ALS, la variable mejor predicha por DAP fue la altura dominante, mientras que los peores resultados se obtuvieron para el número de pies por hectárea. Si bien los modelos basados en ALS predijeron mejor todas las variables excepto H_o , los resultados de ambas tecnologías son comparables en precisión, con diferencias en $RMSE\%$ variando entre -0.35% y 3.31%. Esto es consistente con otros estudios que comparan el desempeño de DAP y ALS para estimar variables de inventario (Bohlin et al., 2012; Gobakken et al., 2015; Noordermeer et al., 2019; Nurminen et al., 2013; Pitt et al., 2014; Ullah et al., 2017; Vastaranta et al., 2013; White et al., 2015). En este estudio sólo se utilizaron variables de altura, dispersiones de altura y cobertura. Sin embargo Bohlin et al (2012)

mostraron que la inclusión de variables de textura extraídas del CHM pueden aportar información adicional a éstas e incrementar la precisión de las estimaciones. Así mismo, el uso de variables espectrales puede ser de utilidad para ajustar modelos específicos de variables dasométricas para cada especie en masas mixtas (Puliti et al., 2017), sin embargo, los pinares estudiados en esta tesis son masas puras y, por tanto, no fue necesario incluir variables de este tipo en los modelos.

Hasta ahora, las comparaciones de ALS y DAP a partir de imágenes de vuelos tripulados en la estimación de variables dasométricas se habían realizado principalmente en bosques boreales de Escandinavia y Canadá (Bohlin et al., 2012; Gobakken et al., 2015; Noordermeer et al., 2019; Pitt et al., 2014; Puliti et al., 2017) y en bosques templados mixtos de Canadá y Alemania (Straub et al., 2013; Ullah et al., 2017; White et al., 2015), así como en plantaciones de *Eucalyptus* y *Pinus radiata* en Tasmania (Caccamo et al., 2018; Iqbal et al., 2019). En España, Felipe (2016) exploró las posibilidades de la DAP a partir de imágenes aéreas generadas mediante un vuelo con paramotor y cámara no métrica en masas de *P. nigra* de la provincia de Albacete. Felipe (2016) demostró que es posible obtener estimaciones de las principales variables dasométricas mediante métodos de masa y cámaras no métricas con resultados similares al ALS. Los resultados de los Capítulos 2 y 3 están en línea con los demás estudios y confirman que los datos DAP de campañas nacionales como el PNOA pueden ser utilizados para caracterizar satisfactoriamente variables de inventario en pinares mediterráneos cuando existan un DTM generado a partir de datos ALS. De esta forma, la DAP puede ser una alternativa al ALS, confirmando la tesis de Kangas et al. (2018b) de que el uso de DAP o ALS depende únicamente de la disponibilidad de datos y los costes de adquisición. La principal ventaja de usar DAP a partir de imágenes tomadas en vuelos tripulados es que en muchos países existen programas de captura de fotografía aérea, y que en el caso de haber también un programa de captura de datos ALS, se realizan en ciclos más cortos y estables que estos.

En el Capítulo 2 se estudian las diferencias entre las nubes de puntos ALS y DAP. La principal diferencia entre ambas tecnologías es la capacidad multirretorno del ALS, lo que le permite ofrecer información del terreno y la vegetación que se encuentra bajo el dosel. Contrariamente, la DAP sólo es capaz de caracterizar la parte más externa del dosel. Por este motivo, en otros estudios se ha observado una menor correlación entre los percentiles más bajos de DAP y ALS y una mayor correlación entre los percentiles altos (St-Onge et al., 2008; Vastaranta et al., 2013; White et al., 2013b). Sin embargo, los resultados de esta tesis muestran que todos los percentiles, tanto los bajos como los altos, estuvieron fuertemente correlacionados entre ALS y DAP (siempre por encima de 0.87), si bien es cierto que hay un aumento significativo de la correlación a partir del percentil h_{10} (0.95). Esto puede deberse

principalmente a dos razones: la menor densidad de pulsos ALS utilizada en este estudio y la menor complejidad estructural de la vegetación. Otra diferencia que se observó entre ambas tecnologías fue la incapacidad de la DAP para detectar pequeños huecos entre las copas de los árboles que el ALS sí pudo hacer, lo cual coincide con los resultados de otros estudios (p.ej. Vastaranta et al., 2013; White et al., 2015). Este hecho dificulta la comparación directa de nubes de puntos ALS y DAP adquiridas en diferentes años para analizar cambios en la cubierta (Vastaranta et al., 2013). De esta forma, por ejemplo, es posible apreciar cierto crecimiento en la vegetación comparando datos ALS y DAP, cuando en realidad se han abierto pequeños huecos en la cubierta debidos a tratamientos selvícolas que la DAP no es capaz de detectar (Vastaranta et al., 2013).

Dada la diferente forma de caracterizar la vegetación por parte de las nubes de puntos ALS y DAP, puede no ser posible aplicar modelos de variables dasométricas ajustados con estadísticos ALS a datos DAP. Por esta razón, en Goodbody et al. (2019) se recomienda construir modelos ABA basados en variables que sean semejantes en ambas tecnologías si se pretende que estos modelos puedan ser utilizados con datos ALS o DAP indistintamente. La alta correlación entre los percentiles de altura de ambas tecnologías observada en el Capítulo 2 motivó que, en el Capítulo 3, se analizara la posibilidad de encontrar variables estables que permitieran generar modelos a partir de estadísticos ALS transferibles a datos DAP. Además, con el fin de encontrar soluciones que faciliten la actualización de inventarios, también se estudió la transferibilidad de modelos entre datos ALS de distintas características y la transferibilidad temporal de modelos entre nubes de puntos DAP adquiridas con distintas cámaras y configuraciones de vuelo.

Los modelos contruidos en el Capítulo 3 demostraron una alta capacidad de transferibilidad gracias al uso de variables estables. Estos modelos fueron transferidos a nuevas fuentes de datos sin pérdidas significativas de precisión ($\Delta RMSE\%$ varió entre - 8.27% y 2.98%). Así, se ha demostrado que no sólo es posible transferir satisfactoriamente modelos temporal y espacialmente entre datos ALS (transferibilidad ALS-ALS) (Domingo et al., 2019; Fekety et al., 2018, 2015; Zhao et al., 2018) y entre datos DAP (transferibilidad DAP-DAP) (Kirchhoefer et al., 2019; Stepper et al., 2017), sino que también es posible crear modelos a partir de variables extraídas de datos remotos 3D que pueden ser aplicados indistintamente usando una u otra tecnología (transferibilidad ALS-DAP). Estos resultados sugieren que es posible reducir el trabajo de campo y, por tanto, abaratar los costes de inventario, lo cual permitiría un mayor aprovechamiento de la alta resolución temporal de datos remotos 3D en lugares con frecuentes campañas fotogramétricas. Los gestores podrán elegir si instalar nuevas parcelas para calibrar modelos de variables dasométricas con los datos 3D de las nuevas campañas o bien aplicar modelos contruidos en inventarios anteriores (Fekety et

al., 2015). De esta forma, en sucesivos inventarios las parcelas pueden servir para validar la transferencia temporal o tecnológica de los modelos. Además, el uso de modelos transferibles puede permitir hacer análisis retrospectivos de variables dasométricas a partir de colecciones de imágenes fotogramétricas antiguas (Filippelli et al., 2019). Por otra parte, la utilización de modelos basados en variables estables puede facilitar la comparación de los resultados con otros estudios, ya que conduce a una armonización de los resultados de inventarios asistidos por diferentes fuentes de datos 3D (Görgens et al., 2015; Kirchhoefer et al., 2019).

La actualización de inventarios y el monitoreo de cambios en la estructura de la vegetación a partir del análisis multitemporal de datos 3D debe realizarse con cautela. Si el periodo de tiempo entre un inventario (T_1) y la actualización de éste (T_2) es corto, puede ocurrir que el error derivado de la estimación de las variables dasométricas sea mayor que el crecimiento de la masa (Stepper et al., 2014b). Esta situación puede darse con frecuencia en bosques de crecimiento lento o muy lento. Sin embargo, en masas de crecimiento rápido o zonas con gestión intensiva en las que se practiquen cortas frecuentemente, la información adquirida mediante el uso de datos 3D multitemporales puede ser suficientemente útil y fiable para estudiar los cambios en la cubierta y el crecimiento de las masas forestales incluso en cortos periodos de tiempo.

Por otro lado, Noordermeer et al. (2019) encontraron en modelos regionales ajustados con diferentes sensores ALS y DAP y configuraciones de vuelo distintas, efectos asociados a cada zona de estudio. Estos efectos se debieron no sólo a las diferencias en la vegetación en cada una de las áreas de estudio, sino también a los problemas que presenta la DAP bajo diferentes configuraciones de vuelo. Rahlf et al. (2017) analizaron la influencia de diferentes variables relacionadas con las características del vuelo y el procesado DAP, como la elevación del sol, el ángulo de incidencia de éste o la pendiente, y hallaron que todas eran significativas, indicando que son factores que han de tenerse en cuenta cuando se construyen modelos con la intención de ser transferibles, y que por tanto no se puede garantizar la transferibilidad de un modelo generado a partir de datos DAP a cualquier nube de puntos DAP. Esto remarca la importancia de la selección de variables estables entre los datos 3D originales con los que se ajusta el modelo y los nuevos en los que se pretende aplicar para maximizar las posibilidades de transferencia del modelo.

Además, las características de las nubes de puntos DAP dependen en gran medida del flujo de procesamiento SfM mediante el que se generan y de los algoritmos que en éste se utilicen. El uso de distintos softwares comerciales con algoritmos propios, en la mayoría de los casos no publicados y con escasas posibilidades de manipulación por parte del usuario,

limita las posibilidades de estandarización de los productos fotogramétricos (Goodbody et al., 2019). Los algoritmos utilizados en estos softwares, que por otra parte no están específicamente diseñados para la generación de modelos 3D de la vegetación, se encuentran en constante evolución, conduciendo a variaciones en la caracterización de la estructura de la vegetación por parte de las nubes de puntos (Gobakken et al., 2015). Los parámetros de procesamiento utilizados para generar las nubes de puntos de los Capítulos 2 y 3 se eligieron para permitir caracterizar los cambios abruptos y frecuentes en la elevación que producen las copas de los árboles. Sin embargo, estos parámetros pueden variar en función del tipo de vegetación, la pendiente o el GSD utilizado.

Finalmente, las nubes de puntos DAP de los Capítulos 2 y 3 fueron normalizadas con DTMs de alta resolución generados a partir de datos ALS. Sin embargo, estos datos, aunque comunes en muchos países europeos y grandes áreas de Norteamérica (White et al., 2013), no son frecuentes en otros lugares del mundo, lo que limita las posibilidades de la DAP como fuente de datos auxiliares en inventarios forestales en estas zonas. Algunas investigaciones realizadas en masas con cobertura espesa han analizado la capacidad de caracterización de la estructura de la vegetación mediante el uso de imágenes de UAV y DAP normalizando la información con DTMs generados a partir de los propios datos fotogramétricos (Dandois and Ellis, 2013; Wallace et al., 2016). Estos estudios demostraron que, pese a la alta densidad de puntos obtenida a partir de imágenes UAV, las estimaciones de las variables analizadas fueron sesgadas. Por otra parte, Giannetti et al. (2018) desarrollaron y testaron con éxito una metodología para la estimación de variables dasométricas mediante métodos de masa a partir de imágenes de UAV y DAP que no precisa normalizar los datos 3D con un DTM. Sin embargo, es de esperar que este método no pueda ser utilizado con imágenes generadas por vuelos tripulados puesto que requiere de nubes de puntos muy densas. Además, la mayor complejidad de las variables utilizadas en este método podría conducir a una limitación en la capacidad de transferibilidad de los modelos (Iglhaut et al., 2019).

En el Capítulo 4 se abandona el análisis de datos 3D generados con cámaras métricas sobre aviones tripulados en la modelización de variables dasométricas mediante métodos de masa, para centrarse en evaluar la utilización de DAP a partir de imágenes de UAV en la detección y medición de variables de árbol individual. Se muestra una nueva metodología para estimar la AGB de plantaciones jóvenes en grandes superficies combinando datos de Sentinel-1 y Sentinel-2, en la que la DAP a partir de imágenes de UAV es utilizada como herramienta para la detección y medición de árboles en parcelas de muestreo. Estos datos se utilizaron después para calibrar modelos a partir de datos radar y multiespectrales con los que estimar la AGB mediante estimadores del model-assisted

La metodología utilizada combinando DAP e ITC para la medición de árboles individuales sobre nubes de puntos 3D generadas con un UAV de bajo coste, supone una forma eficiente, económica y operativa para sustituir el trabajo de campo en zonas remotas y muchas veces impracticables como son los manglares. El terreno plano y la apertura de la vegetación permitió que se encontraran suficientes puntos correspondientes con el suelo, por lo que se pudo utilizar DAP para crear un CHM de cada parcela de inventario sin necesidad de normalizar la información tridimensional con un DTM generado a partir de datos ALS (Guerra-Hernández et al., 2016; Jensen and Mathews, 2016; Mohan et al., 2017). La detección de árboles se llevó a cabo mediante un proceso semiautomático a partir de los CHM con distintos tamaños de ventana debido a los diferentes tamaños de vegetación en cada una de las parcelas. Al tratarse de un método semiautomático, con revisión visual de los resultados en base a las ortofotos de alta resolución generada a partir de los vuelos UAV en plantaciones más o menos abiertas y con una distribución homogénea de los pies, se asumió que no se cometieron errores por omisión ni comisión en la detección de pies. Sin embargo, la precisión en la detección de árboles es un factor importante a tener en cuenta en otros tipos de masa, en los que la complejidad estructural dificulte este proceso. Mohan et al. (2017) alcanzaron una tasa de detección del 91.6%, con errores por omisión y comisión del 5.7% y 2.7%, respectivamente, en una masa abierta mixta de coníferas en Estados Unidos. En cambio, Guerra-Hernández et al. (2018) obtuvieron tasas de detección del 79.6% en plantaciones densas de *Eucalyptus* spp., con errores por omisión y comisión en el mejor de los casos del 20.8% y 6.5%, respectivamente.

Los resultados del Capítulo 4 muestran que la altura y el diámetro de copas se midieron con niveles altos de precisión y, por tanto, pudieron ser utilizadas para hacer estimaciones precisas de la AGB de parcelas de muestreo en el área de estudio. Sin embargo, las estimaciones de la AGB fueron conservadoras debido a que la medición de las alturas de los pies fue negativamente sesgada al igual que en otros estudios que utilizan ITC con datos DAP (Guerra-Hernández et al., 2018; Mayr et al., 2017; St-Onge et al., 2004). Las estimaciones de AGB a nivel de parcela se utilizaron para predecir la AGB media de cada estrato y de toda el área de estudio mediante estimadores propios de la inferencia basada únicamente en el diseño del muestreo y los estimadores del model-assisted. Para utilizar estos últimos, se ajustaron modelos SVR usando como información auxiliar variables extraídas de datos radar y multiespectrales de Sentinel-1 y Sentinel-2. Los resultados mostraron que la utilización de modelos basados en la combinación de ambos sensores mejoró un 115% la eficiencia del inventario. Esto quiere decir que, asumiendo un muestreo aleatorio simple, se necesitaría un 115% más de parcelas UAV para alcanzar el mismo error estándar en la estimación de la AGB media de la zona de estudio, confirmando que el uso combinado de información de ambos satélites mejoró notablemente las estimaciones de AGB y

permitió trabajar en un área muy extensa y remota de forma económica y eficiente. El marco de inferencia utilizado permitió usar estimadores insesgados basados en el diseño de muestreo. De esta forma, aunque los modelos no fueran robustos, los estimadores de la media y del total seguirían siendo insesgados, ya que éstos no dependen de la bondad del modelo (Särndal et al., 1992; Ståhl et al., 2016).

Capítulo 6. Conclusiones

Esta tesis ha analizado la utilización de la DAP en la estimación de variables dasométricas a partir de imágenes aéreas tomadas desde vuelos tripulados en campañas fotogramétricas y desde UAVs. Para ello, se ha respondido cada una de las preguntas de investigación planteadas:

- I. *¿Qué similitudes y diferencias tienen las nubes de puntos generadas mediante DAP y ALS?*
 - I.1. Las nubes de puntos DAP caracterizan la vegetación de forma diferente a las nubes de puntos ALS. La principal diferencia es la incapacidad de la DAP para caracterizar completamente la distribución vertical de la vegetación debido a la falta de penetrabilidad en la cubierta. Por este motivo, en masas cerradas, es necesario utilizar DTMs generados a partir de datos ALS para normalizar las nubes de puntos DAP.
 - I.2. Las copas de los árboles se aprecian de forma más difusa y redondeada en las nubes de puntos DAP que en las ALS debido a que la primera es menos sensible en la detección de los ápices de los árboles y pequeños huecos en la cubierta. Por este motivo, los pequeños cambios en la estructura de la vegetación pueden no ser detectados mediante una comparación directa de nubes de puntos de ambas tecnologías.
 - I.3. En el Capítulo 2 de esta tesis se observó una fuerte correlación entre los percentiles de altura DAP y ALS, sobre todo en los más altos. Por el contrario, las variables de dispersión de altura y cobertura tienen una menor correlación entre ambas tecnologías debido a la falta de penetrabilidad de la DAP bajo el dosel.
- II. *¿Pueden usarse imágenes aéreas de campañas nacionales como el PNOA como fuente de datos alternativa a ALS en la estimación de variables de inventario?*
 - II.1. Las imágenes aéreas de campañas nacionales pueden utilizarse para estimar diferentes variables dasométricas en pinares mediterráneos utilizando ABA. Los resultados del Capítulo 2 de esta tesis fueron del mismo orden de magnitud que otros estudios similares llevados a cabo en otros tipos de bosque utilizando imágenes de vuelos tripulados. Los modelos basados en estadísticos DAP predijeron todas las variables de forma ligeramente menos precisa que los modelos basados en datos ALS, excepto en el caso de la altura dominante. De esta forma, las imágenes aéreas de campañas nacionales pueden ser una fuente de datos

alternativa de datos 3D en zonas donde existen datos ALS previos con los que normalizar las nubes de puntos DAP.

III. *¿Es posible generar modelos que sean transferibles entre datos 3D tomados con la misma tecnología y diferentes características? ¿Y usando ALS y DAP indistintamente?*

III.1. En el Capítulo 3 se ha utilizado un nuevo método de selección de variables para construir modelos SVR a partir de estadísticos estables entre las diferentes fuentes de datos 3D utilizadas. El uso de estas variables permitió la transferibilidad de modelos entre datos generados en diferentes momentos en el tiempo con la misma tecnología, pero con sensores y parámetros de vuelo distintos (transferibilidad ALS-ALS y DAP-DAP), y entre datos generados con tecnologías diferentes (transferibilidad ALS-DAP) sin pérdidas significativas de precisión.

III.2. Las variables relacionadas directamente con la altura de la vegetación fueron más estables que las variables de dispersión de altura y cobertura. En concreto, h_{mean} fue la variable más estable entre todas las fuentes de datos 3D utilizadas.

III.3. Se necesita más investigación para validar los resultados de este estudio en otras zonas y en nubes de puntos generadas con otros algoritmos fotogramétricos y/o diferentes configuraciones de vuelo.

III.4. El uso de modelos transferibles en el tiempo y entre tecnologías puede contribuir a un mejor aprovechamiento de la disponibilidad de datos 3D para desarrollar métodos de inventario continuos y dinámicos gracias a la reducción en las necesidades de trabajo de campo.

IV. *¿Puede calcularse la biomasa aérea en parcelas de muestreo mediante métodos de árbol individual a partir de imágenes de UAV?*

IV.1. La metodología semiautomática utilizada permitió una correcta detección y delineación de las copas de todas las plantas de mangle localizadas en las parcelas de inventario.

IV.2. Los resultados de la validación independiente mostraron que la altura de los pies y el diámetro de copa pueden ser medidas sobre nubes de puntos DAP generadas a partir de imágenes UAV con precisiones aceptables, si bien ambas variables fueron ligeramente subestimadas. De esta forma, se obtuvieron mediciones conservadoras de AGB en las parcelas de inventario.

IV.3. La metodología utilizada permite un aumento del rendimiento en la medición de parcelas de inventario en áreas remotas o poco practicables como los manglares. Sin embargo, es necesario testar esta metodología en zonas de vegetación más densa donde la detección y delineación de las copas de los árboles es más difícil.

V. *¿Mejora las estimaciones de biomasa aérea utilizar datos satelitales radar y multiespectrales como información auxiliar?*

V.1. La combinación de datos radar y multiespectrales de Sentinel-1 y Sentinel-2 produjo redujo sustancialmente el error en la estimación de la media poblacional de AGB, especialmente en el estrato con vegetación de mayor tamaño. El error estándar en la estimación de la AGB para toda el área de estudio fue un 31.7% más bajo en comparación con la estimación basada únicamente en las parcelas UAV.

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