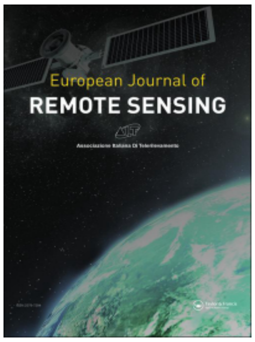

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European Journal of Remote Sensing

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tejr20

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To cite this article: Juan Guerra-Hernández, Adrian Pascual, Frederico Tupinambá-Simões, Sergio Godinho, Brigite Botequim, Alfonso Jurado-Varela & Vicente Sandoval-Altelarrea (2024) Using bi-temporal ALS and NFI-based time-series data to account for large-scale aboveground carbon dynamics: the showcase of mediterranean forests, European Journal of Remote Sensing, 57:1, 2315413, DOI: 10.1080/22797254.2024.2315413

To link to this article: https://doi.org/10.1080/22797254.2024.2315413

Published online: 18 Feb 2024.

EUROPEAN JOURNAL OF REMOTE SENSING
2024, VOL. 57, NO. 1, 2315413
https://doi.org/10.1080/22797254.2024.2315413

Using bi-temporal ALS and NFI-based time-series data to account for large-scale aboveground carbon dynamics: the showcase of mediterranean forests

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ABSTRACT

New remote-sensed biomass change products will transform our capacity to monitor and validate large-scale carbon dynamic in the next decade. In this study, we evaluated the use of multitemporal Airborne Laser Scanning (ALS) and the Climate Change Initiative (CCI) BIOMASS spaceborne mission to estimate AGB dynamics in different Mediterranean forest over an 8-year period (2010–2018). To do so, we evaluated different maps to estimate change in AGB, specifically indirect approach using forest-type specific ALS-based AGB maps using i) countrywide ALS coverage at 25 m resolution (2010–2018) and ii) the global, 100-m resolution CCI maps version 3 (2010–2018). The change in AGB (ΔAGB) was mapped across the study region to compute dynamics by forest type. Our results suggest that the indirect approach using ALS-model-based produced more accurate estimates in change of AGB than CCI when we compared with the design-based AGB estimation using Spanish National Forest Inventory (SNFI) at strata level. The spatial representation of the AGB change indicated that ΔAGB-ALS changes by forest type had an overall gain in biomass at regional level. The ΔAGB total and net annual changes by year and area (ΔAGB, Mg ha^{-1} $year^{-1}$) were closed to the values obtained using SNFI at strata level. This study demonstrates the feasibility of enhancing carbon sequestration and stock capacity in Mediterranean forest using multitemporal ALS data and the limitations of global AGB maps at Regional Scale.

ARTICLE HISTORY
Received 24 May 2023
Revised 8 September 2023
Accepted 1 February 2024

KEYWORDS
LiDAR; CCI biomass mission; forest monitoring; biomass stocks; Spanish National Forest Inventory (SNFI); carbon sequestration

Introduction

Forest information on aboveground biomass (AGB) is particularly important to support local, regional and national forest planning strategies. The capability of forests to act as carbon pools makes them a key actor to reduce CO2 concentration in the atmosphere since they absorb 30% of the total CO2 emitted into the atmosphere globally by year (Houghton & Nassikas, 2017; Vangi et al., 2022). While other carbon pools such as soil organic matter, roots and understory vegetation can store huge amounts of biomass, quantification of these reservoirs is more difficult and expensive (Fahey et al., 2010; Kilpeläinen & Heli, 2022; Pérez-Cruzado et al., 2012). The carbon sequestration in AGBD stocks is the most dynamic carbon sink in forests and might fluctuate greatly in a forest ecosystem during a period of time (Routa et al., 2019). Therefore, AGB has a central role to fight climate change and anthropogenic emissions by maintaining the global climate balance since AGB represents nearby 30% of the total carbon sink from terrestrial ecosystems (Eggleston et al., 2006; Kumar & Mutanga, 2017). Despite their importance, there is a lack of knowledge about large-scale carbon dynamic from Mediterranean forest ecosystems in Europe, and incomplete knowledge concerning their functions in the global carbon cycle (Keenan et al., 2015). A better understanding of the AGB stocks in Mediterranean forests is also essential for optimizing land carbon sequestration policies (Guerra-Hernández et al., 2016; Pascual et at., 2021; Guerra-Hernández, Botequim, et al., 2022; Guerra-Hernández, Narine, et al., 2022).

Following the recommendations of The Intergovernmental Panel on Climate Change (IPCC), a combination of field-based inventory plots and Earth Observation (EO) data should be used to estimate temporal and spatial changes in carbon stocks and

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forest area (Espejo et al., 2020). Various approaches have been applied to report forest biomass stocks and fluxes which depend on the technical and financial support at national level with different levels of information (Rozendaal et al., 2022a, 2022b). AGDB can be computed using Spanish national forest inventory (SNFI) through repeated measurements from plots to estimate biomass change (Alberdi et al., 2017; Álvarez-González et al., 2014; Eggleston et al., 2006; MITECO, 2020). Traditionally, forest carbon stocks have been estimated with SNFI plots by using tree forest variables (diameter, height and wood density) to apply allometric equations (Montero et al., 2005; Ricardo et al., 2012; Ruiz-Peinado et al., 2011). Assessing carbon stock changes between multi-dates NFIs is crucial to complete the reports and requirements of an inventory of anthropogenic greenhouse gases (GHGs) emissions and removals by all the carbon pools at national scale (Vangi et al., 2022). However, NFI has certain limitations: (i) They are not designed to provide reliable estimates for geographic sub-populations using traditional design-based inference due to the smaller sample size networks (Guerra-Hernández, Botequim, et al., 2022), (ii) the NFI may be cost-inefficient to generate forest inventory information over large spatial scales with high frequency (Karimon et al., 2022) and (iii) large cycles of NFIs cannot achieve the required international reporting frequency of two-year carbon stock change in the context of United Nations Framework Convention on Climate Change (UNFCCC) following IPCC guidelines (McRoberts et al., 2018).

On the other hand, integrate remotely sensed (RS) data in the methods could help get over the above-mentioned problems related to spatial and temporal factors of field AGB data (Liu et al., 2023). Spatially continuous information on forest 3D structure is needed to better resolve forest biomass distribution (Saarela et al., 2020). Some studies have demonstrated the potential of using multitemporal ALS data to accurately estimate AGB and its change along time from global to more local showcases (Cao et al., 2016; Hudak et al., 2012, 2020; Mauro et al., 2019; Poudel et al., 2018; Zhao & Popescu, 2009). However, there are very few studies that show the evaluation of AGB at fine-scale resolution over large-scale areas and a lack of knowledge about the accuracy of estimating AGB change and carbon flux using repeated countrywide ALS coverage in Mediterranean forest. Otherwise, numerous AGB-global maps have been created in the last decade, but they are still imprecise for climate and carbon cycle modelling (Arnan et al., 2022). Global maps of AGB are becoming increasingly available from spaceborne satellite missions (Dubayah et al., 2022; Harris et al., 2021; Labrière et al., 2022; Santoro & Cartus, 2021; Yang et al., 2020). Consistent methods and a fair evaluation of global AGB products are of increasing importance (Abbas et al., 2020; Arnan et al., 2022; Bastos et al., 2022; Hunka et al., 2023). Factors such as scale, tree allometries, remote sensing technology must be carefully compared to existing AGB data (Karimon et al., 2022). Thus, it is important to assess the accuracy of global-AGB map, in order to determine the consistency and uncertainty of the map at more local scale (McRoberts et al., 2022; Persson & Ståhl, 2020).

Transparent, consistence and accurate estimations of Mediterranean forest AGB stocks are important in determining the contribution in global carbon dynamics of the Mediterranean forests. This study aims to evaluate the utility of multitemporal ALS data to account for large-scale aboveground carbon dynamics carbon dynamics in Mediterranean Forest. This paper provides a framework to compare AGB-maps estimates from CCI biomass products, AGB-ALS maps, and NFI research plots that account for capacity to estimate biomass change at regional level. The main of objectives of this study were *(i)* generate spatial estimates of AGB and changes (ΔAGB) in large Mediterranean forests area using multitemporal ALS-AGB-based maps, (*ii*) evaluate the capability of Mediterranean forests to store biomass by using the ALS-based and design-based estimations using SNFI and ALS data in different forest ecosystems and (*iii*) comparing AGB and ΔAGB using CCI Global AGB maps v3 product in order to assess the usefulness of global maps for AGB estimations at Regional scale.

Data and methods

Study area

Extremadura Region is located in the south-west of Spain. The Region is the fifth largest of the Spanish autonomous communities with a total area of 41,633 km^2. The forested area covers 19,744.15 km^2 (Figure 1). Eight Forest types from the Spanish Forest Map of Spain (SFM) (E:1:25000) (MAPA, 2018) and the Spanish National Forest Inventory (SNFI) sampling desing were used for this study (MAGRAMA, 2017). They cover an area of 18,335.41 km^2 i.e. 92.54% of the whole forest area (Table 1). *Dehesas* and *Montados* are the largest formation areas with a 67% of the total forested area, followed by *Quercus ilex* formation (*Encinares*) and *Pinus Pinaster* with 9.9% and 4.41%, respectively. We excluded the formation of deciduous oak forests dominated by *Quercus faginea*

Table 1. Summary table of the forest types evaluaed in this study.

Code		Forest type (FT) main species and description	Sup IFN4 (ha)
L101	*Dehesas*	*Quercus* spp. forest with low tree density,canopy cover > 10% and less than < 20%, extensive agrosilvopastoral activity and the presence of sparse old-growth over mature oak forests (*Quercus spp.*)	1323262.86
L102	*Encinares*	*Quercus ilex* subsp. ballota (Desf.) Samp) forest without agrosilvopastoral activity and the presence of Middle-age oak forest and young stands	196054.13
L103	*P.Pinaster*	*Pinus pinaster;* Mediterranean resin pine forests	87088.14
L104	*Mixed forest Quercus ilex*	Mixed forest of *Quercus ilex* and other species broadleads	70596.85
L107	*Eucalyptus spp.*	*Eucalyptus spp.* forest	57822.57
L108	*Alcornocales*	*Quercus suber*	56898.69
L109	*P.pinea*	*Pinus pinea L.* managed for cone production	30664.50
L115	*Mixed conifers forest*	Mixed coniferous forest	4752.10

and *Quercus pyrenaica* species since some part of ALS coverage in Extremadura North from the second ALS flight were obtained under leaf-off conditions in the winter (Sophie et al., 2020) and leaf-on conditions during the summer for the first ALS flight. We selected the following eight Mediterranean forest types to analyse in this study (Table 1)

Design-based estimations AGB at regional scale using SNFI3 and SNFI4 plots

1872 permanent circular plots with 50 m of diameter from the sampling desing of SNFI were used from SNFI3-SNFI-4 (Figure 1, Table 2). The design-based inference method SNFI-3-4 established permanent plots using 1 km x 1 km grid inside of forested areas of SFM. For further details about the SNFI-4 field data and processing, see Álvarez-González et al., (2014) and Dorado-Roda et al. (2021).The AGB stock estimates for the stock-difference method were estimated using only SNFI plots marked with iron poles with the centre of each plot located correctly with a metal detector between SNFI3-SNF4 (called "A1" in SNFI field data protocol). Species-specific tree-level allometric equations used by the SNFI (Montero et al., 2005; Ricardo et al., 2012; Ruiz-Peinado et al., 2011) were used to compute the AGB at time T1(2002) and time T2 (2017), respectively, and then aggregated to units per surface area at plot level (AGBD) The IPCC

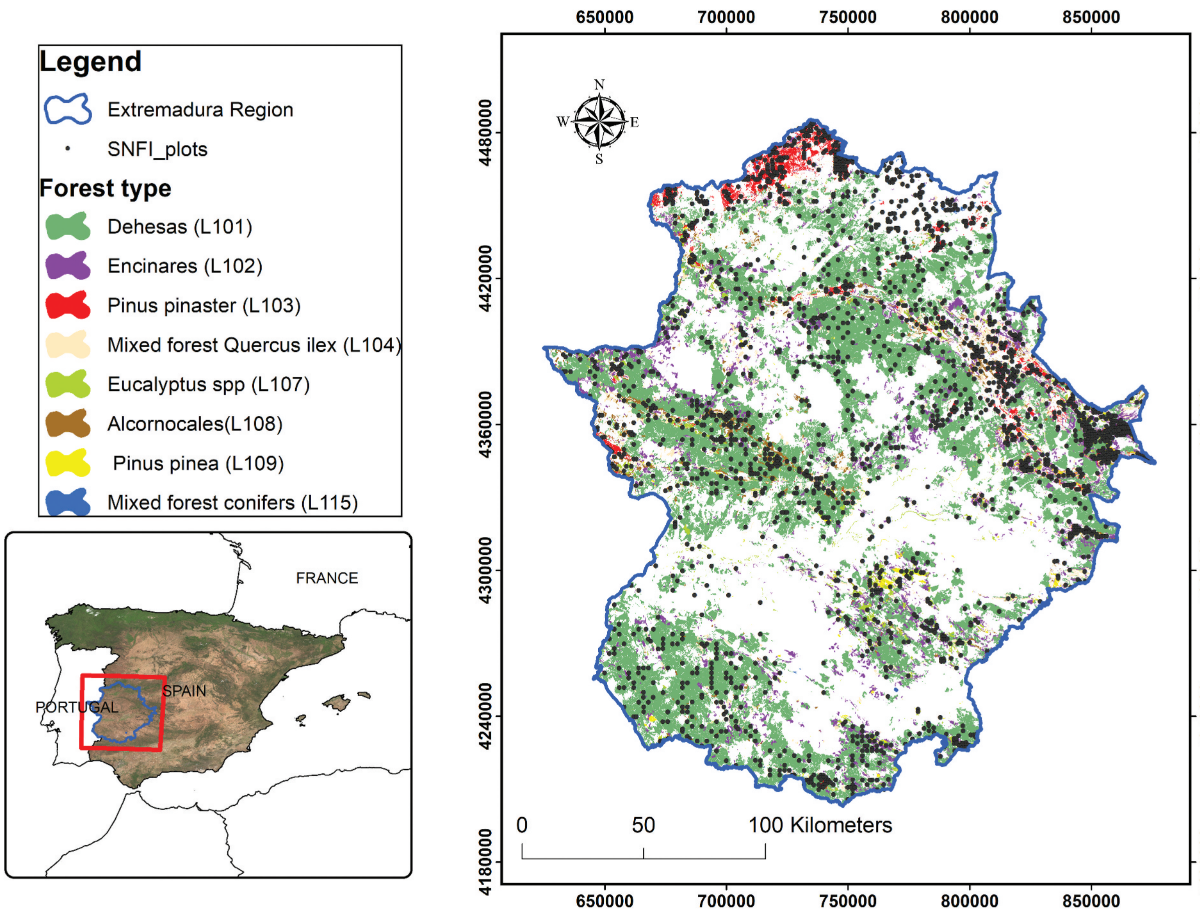

Figure 1a.

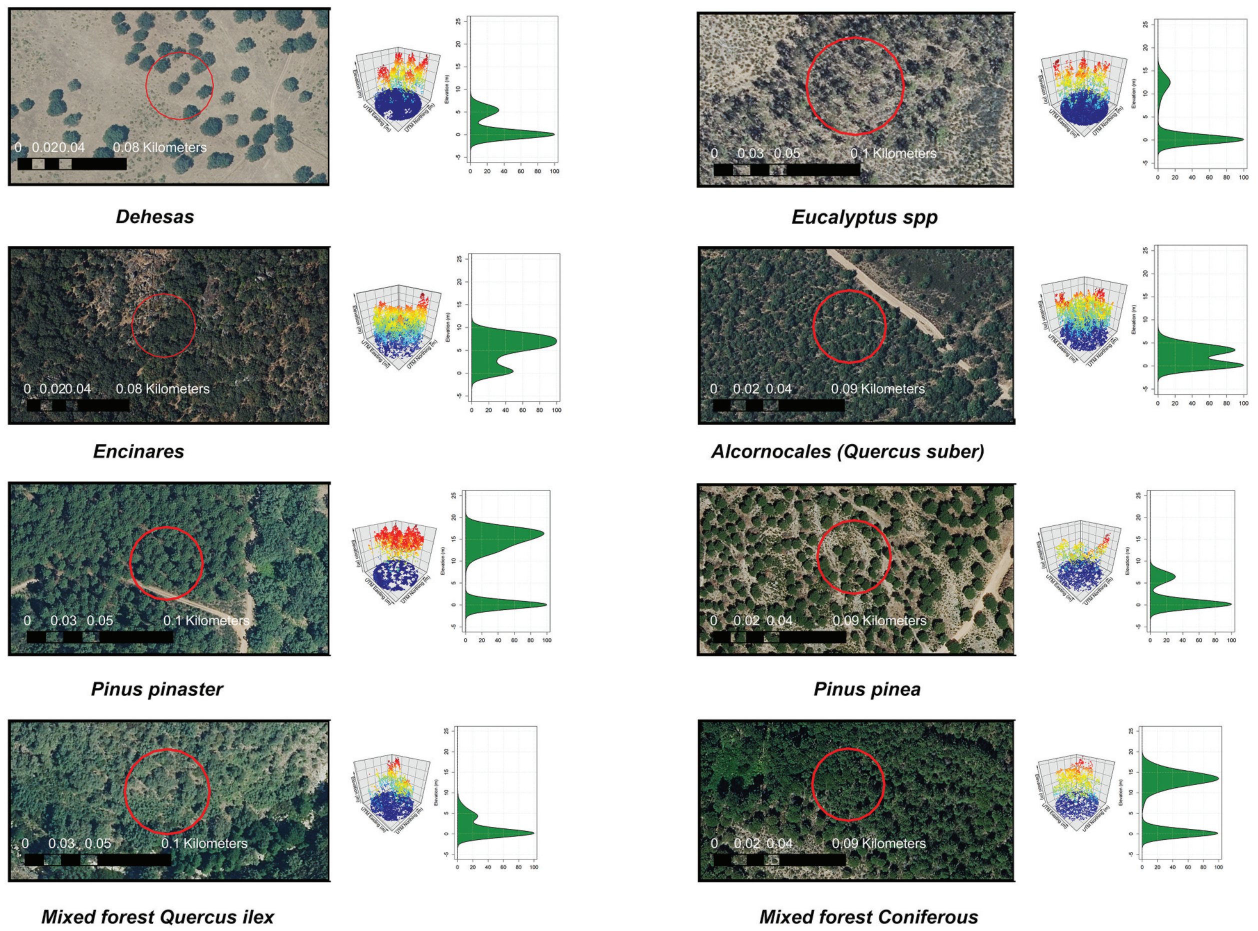

Figure 1b. (a) Extremadura region limits (orange lines) and SFM showing the eight forest types strata and SNFI plots (black dots) evaluated in this study). (b) Examples of the main forest strata modelled in Extremadura and associated extracted ALS point cloud and distribution of point cloud heights from ALS.

Table 2. Summary of ground data collected in the 3th and 4th Spanish National Forest Inventory (SNFI) for the eight forest types considered. The mean values are referred at strata-level estimates for aboveground biomass (AGB, Mg ha^{-1}), change ΔAGB total (mg ha^{-1}), change ΔAGB total by year and change ΔAGB net (mg ha^{-1} year^{-1}) using design-based inference.

Forest type	number of SNFI3-SNFI4 plots	AGB SNFI3 (Mg ha^{-1})	AGB SNFI4 (Mg ha^{-1})	ΔAGB change total (Mg ha^{-1})	ΔAGB change total (Mg ha^{-1} year^{-1})	number of net change SNFI3-SNFI4 plots	ΔAGB net change (Mg ha^{-1} year^{-1})
L101	613	36.84	41.75	4.91	0.31	436	0.65
L102	150	18.81	23.80	6.99	0.44	131	0.60
L103	271	40.10	57.89	17.79	1.19	211	1.91
L104	63	20.82	28.66	8.03	0.50	54	0.74
L107	189	26.94	30.24	3.30	0.22	147	0.85
L108	75	32.78	39.19	6.25	0.39	55	0.79
L109	155	39.31	58.70	19.13	1.28	125	1.84
L115	34	57.87	66.23	8.36	0.54	34	2.21

L101: Dehesa-Montado; L102: Encinares; L103: *P.pinaster;* L104: Mixed forest *Quercus ilex*; L107: *Eucalyptus* spp.; L108: Q. suber; L109: P.pinea; L115: Mixed conifers forest.

guidelines differentiates between two approach to estimated annual rates of change in all carbon pools (Espejo et al., 2020). We used the AGB stock-difference method using the difference in total AGB stocks at two points in time divided by the number of intervening years. For calculation of design-based estimates, stratified estimation required two steps: (i) assigning of each SNFI plot to a single stratum, and (ii) calculation of the strata weights as the relative proportions of the population area corresponding to SFM strata.

The AGB estimated for design-based inference for SNFI 3 (2002) and SNFI4 (2017) are listed in Table 2 using the time interval as the period of measurements between the plots. Multi-dates SNFIs plot permits the calculation of ΔAGB (Mg ha^{-1}) change plot as the difference between the AGB stock at T2 and T1. The ΔAGB total changes (Column 6, Table 2) were calculated at strata level using design-based estimations from SNFI3 and SNF4 considering permanent plots with or without and natural disturbances. The ΔAGB total changes by year and area (Colum 7, Table 2) were calculated by dividing ΔAGB total changes by the period of measurements between the plots. In the case of ΔAGB net changes by year and area (Column 9, Table 2) we considered only the plots that have not been suffered silvicultural operations or natural disturbances into the SNFI plots to extrapolate the values at strata level. Only sample plots (Column 8, Table 2) showing non-negative increments in terms of basal area between the 3rd and 4th SNFI were used to control the bias from selvicultural and natural disturbances (Bolton et al., 2013).

AGB-ALS and CCI Global AGB maps v3

Data from two ALS point clouds were collected for T1 and T2 in the study: the first ALS data set from the north of Extremadura (EXT-N) was collected between August 2010 and July 2011 and between October 2018 and March 2019, whereas south of Extremadura (EXT-S) was acquired between October 2009 and September 2010 and between October 2018 and July 2019. The methodology and performance of ALS-AGB models used to produce AGB maps at regional level for each forest strata are described in Guerra-Hernández, Botequim, et al., (2022). More specific technical characteristics of ALS flights can be found in PNOA LiDAR project (Plan Nacional de Ortofotografía Aérea). (https://pnoa.ign.es/el-proyecto-pnoa-lidar). We used an indirect approach to extrapolate a model generated for one date (validated with field data) to another date. The strata from SFM and previously published ALS-based models of AGB (Appendix A (Table A.1 in Guerra-Hernández, Botequim, et al., 2022) were used to generate a regular 25 m resolution AGB-ALS-based map at the regional scale (Extremadura) (Figure 2(a,b) for 2010 and 2018. The different point density may affect model

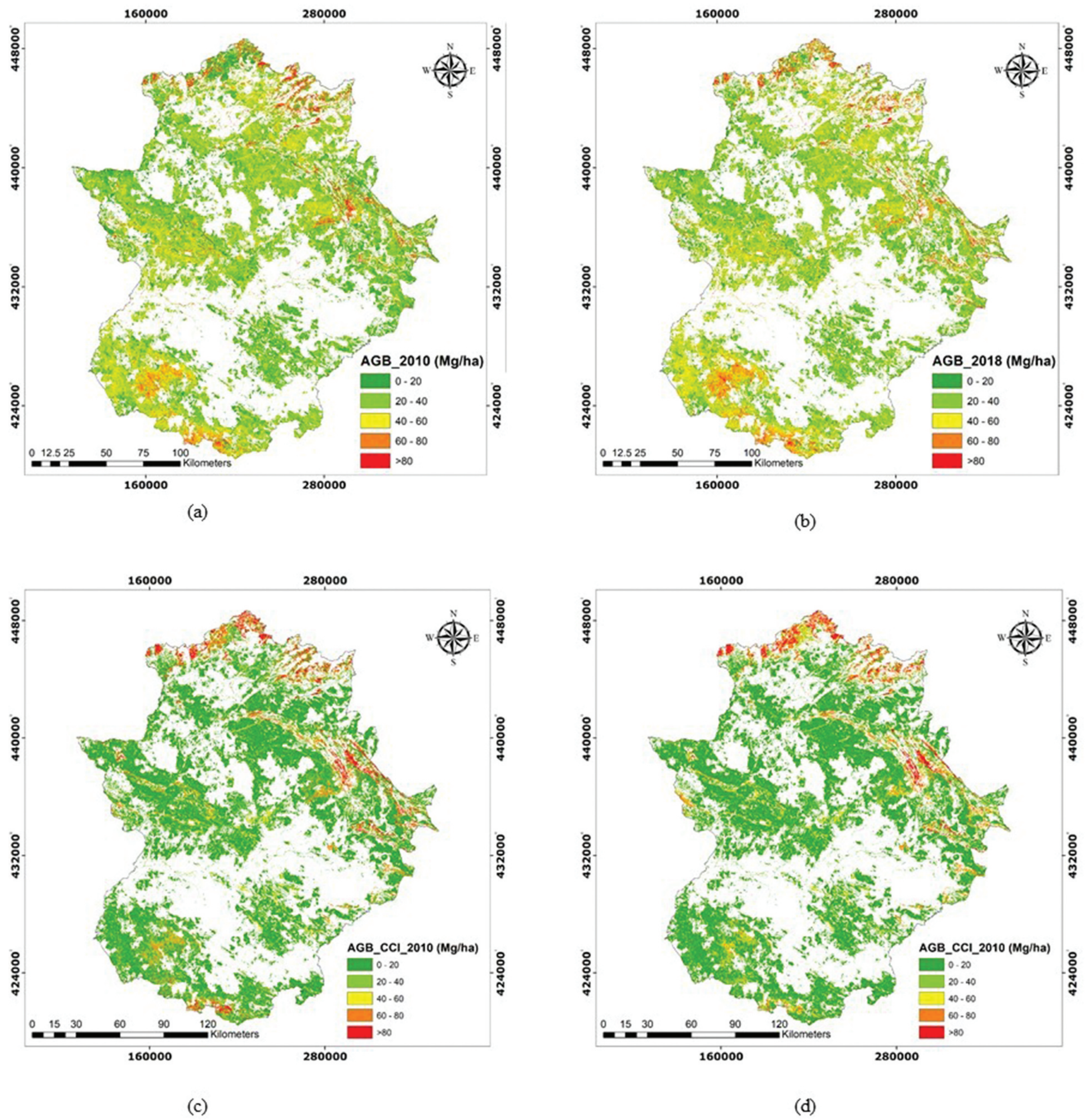

Figure 2. AGB-ALS maps (year 2010 (a) and 2018 (b) developed under model-based inference using area-based approach (ABA) for each forest stratum. CCI biomass map 2010 (c) and 2018(d) version 3.

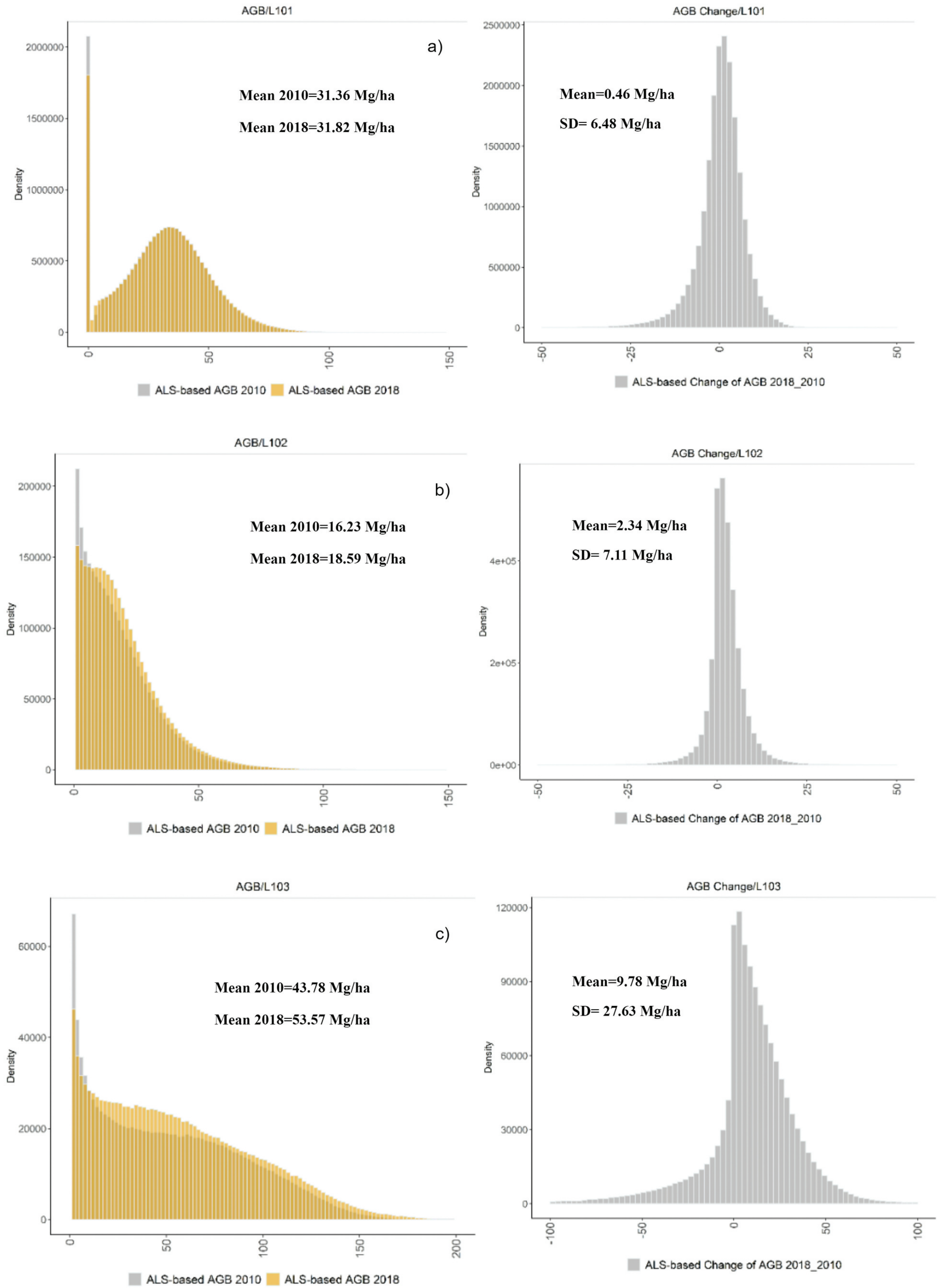

Figure 3a.

performance but did not have a significant impact in forest variables estimations as ALS-3D point clouds has a stable vertical pattern (Cao et al., 2016). On the other hand, the model temporal transferability has been evaluated by several studies with satisfactory results (Domingo et al., 2019; Marino et al., 2022; Tompalski et al., 2019) using low-density ALS-Spanish-PNOA project with different point density

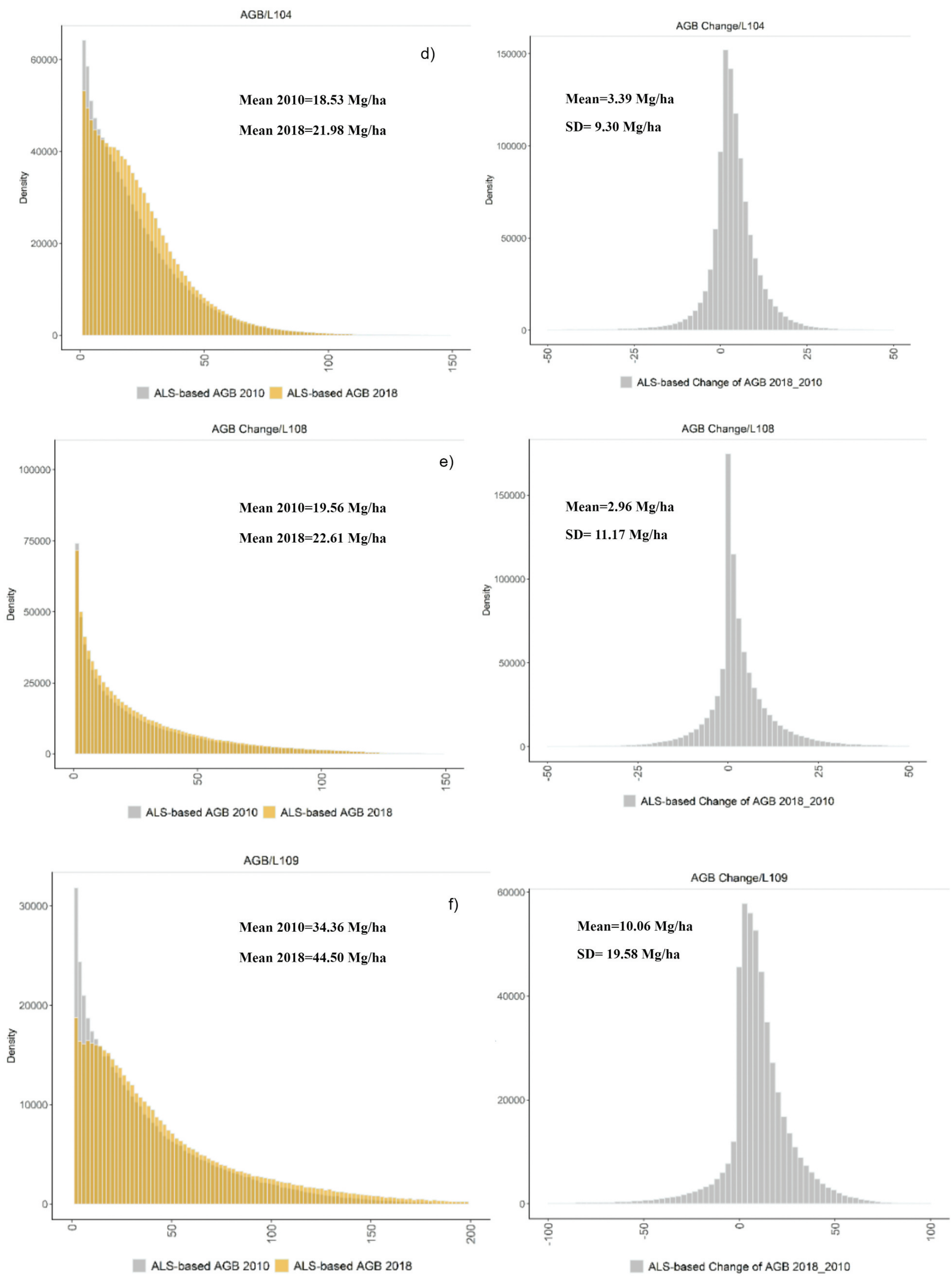

Figure 3b. Methodological scheme of the study.

for two different points in time. Domingo et al., 2019 found good temporal transferability, the average % RMSE differences between the fitted and the extrapolated AGB model was 5.85%, even lower than the models fitted 2011 (lower density) and extrapolated to 2016 (high density). The ΔAGB changes were calculated at strata level using estimations from T1 and T2 at pixel level. In the case of ΔAGB net changes by year and area, increment was calculated considering only the 25-m pixel values showing positive increments of AGB and divided for a period of 8 years (2010–2018). The ALS-model-based uncertainty in terms of relative standard error for AGB by forest type is described in Guerra-Hernández, Botequim, et al., (2022).

CCI data portal (https://climate.esa.int/en/odp/#/project/biomass) was used to download available CCI BIOMASS products. The CCI Global datasets v3 provides estimates of AGB for the years 2010 and 2018, respectively (Santoro & Cartus, 2021). A combination of EO data from the Copernicus Sentinel-1 mission, Envisat's ASAR instrument and JAXA's Advanced Land Observing Satellite (ALOS-1 and ALOS-2) with additional information from Earth observation sources were used to generate the maps. The strata from SFM were used to clip the CCI biomass map to compute the AGB statistics at Regional level using original resolution of 100 m.

Methods

A detailed flowchart is shown in Figure 4. The study was guided by the following specific objectives: *i)* generate spatial estimates of AGB and changes (ΔAGB) in large Mediterranean forests area using multitemporal ALS-AGB-based maps, (*ii*) evaluated the capability of Mediterranean forests to store biomass by using the ALS-based and design-based estimations using SNFI and ALS data and (*iii*) comparing AGB and ΔAGB using CCI Global AGB maps v3 product in order to assess the usefulness of global maps for AGB estimations at Regional scale Figure 3.

Results

AGB and ΔAGB estimated from ALS

The ALS-based estimates of AGB stocks and the ΔAGB changes using the bi-temporal ALS-AGB maps data varied by forest type (Table 3, Figure 4). The even-age mature pine stands (typically dominated by *Pinus pinaster* and *Pinus Pinea*) achieved a mean value of total ΔAGB = 9.78 Mg ha^{-1} and 10.06 Mg ha^{-1}, respectively, during the period of 8 years across the Region. *Encinares* (L102) with the presence of young stands from new reforestations and natural regeneration showed noticeable growth of biomass during the period of 8 years (mean ΔAGB = 2.34 Mg ha^{-1}). *Dehesas* (L101) with the presence of more overmature stands (typically dominated by sparse old-growth holm forests (*Quercus* spp.) with low tree

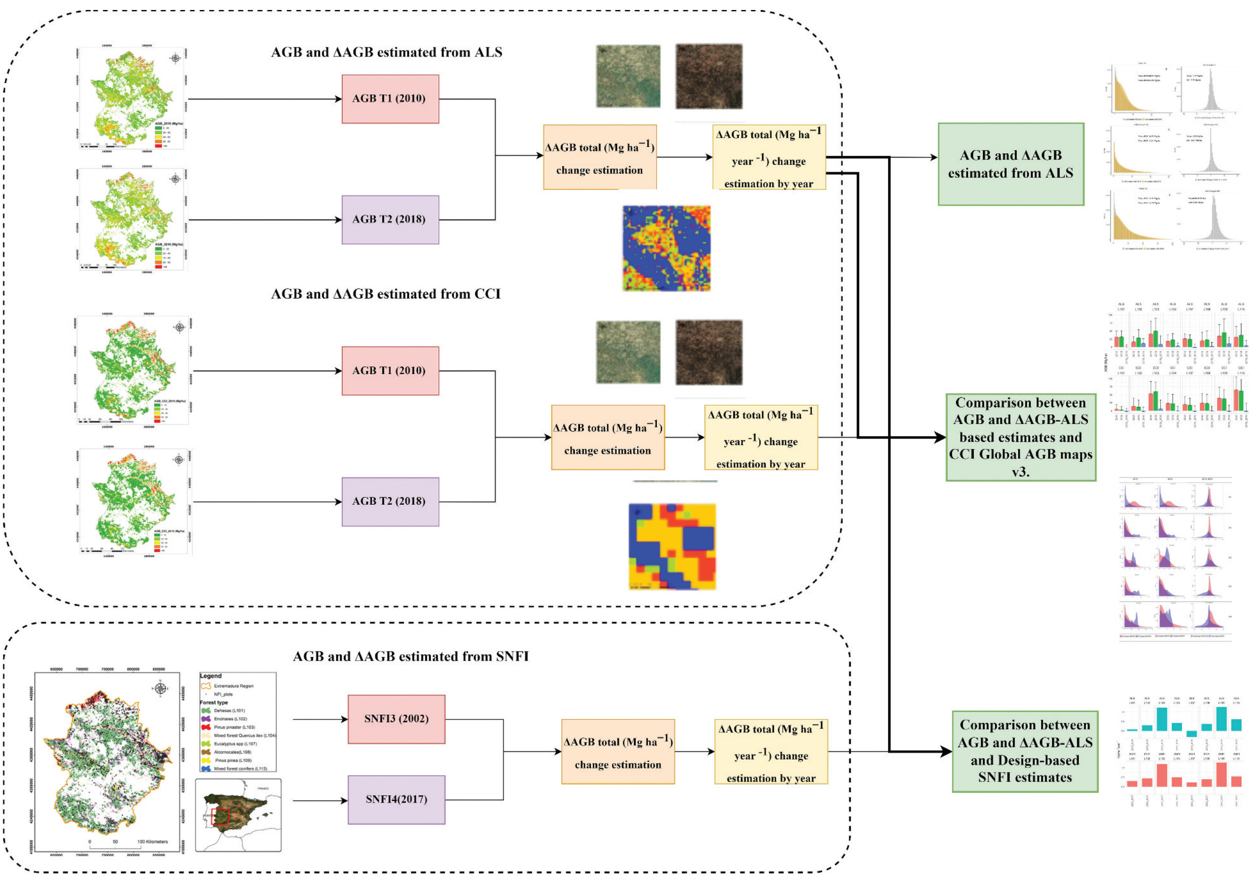

Figure 4. Histogram AGB distributions across the research site from 2010 to 2018 for the main forest strata at regional level and the change between the two times for dehesas (a), Encinares (b), P. pinaster (c) mixed forest quercus ilex (d), Alcornocal (e) and P. pinea (f).

Table 3. Summary of statistical analysis results for ALS-derived AGB in 2010, 2018 and their change estimation total ΔAGB (mg ha^{-1}), change ΔAGB total by year (mg ha^{-1} year $^{-1}$) and ΔAGB net (mg ha^{-1} year $^{-1}$) from each forest type including pixel values with AGB = 0.

AGB (Mg ha^{-1}) estimation 2010								
Strata	L101	L102	L103	L104	L107	L108	L109	L115
n	21165912	3136397	1391193	1129576	923977	910064	490602	76040
Mean	31.36	16.23	43.78	18.53	26.68	19.56	34.36	32.81
SD	18.44	16.47	39.97	20.33	14.50	26.38	35.82	34.22
Median	31.95	12.39	35.39	12.87	26.58	8.47	23.04	22.62
CV	0.59	1.01	0.91	1.10	0.54	1.35	1.04	1.04
AGB (Mg ha^{-1}) estimation 2018								
Mean	31.82	18.59	53.57	21.98	24.35	22.61	44.50	37.09
SD	18.55	16.78	41.30	20.17	13.90	26.72	42.76	35.44
Median	32.27	16.10	47.04	17.65	23.01	12.63	31.42	26.62
CV	0.58	0.90	0.77	0.92	0.57	1.18	0.96	0.96
ΔAGB total (Mg ha^{-1}) change estimation								
Mean	0.46	2.34	9.78	3.39	−2.53	2.96	10.06	4.89
SD	6.48	7.11	27.63	9.30	11.48	11.17	19.58	14.97
Median	0.53	2.02	9.25	2.94	−0.47	1.23	8.52	4.00
CV	14.02	3.03	2.83	2.74	−4.53	3.78	1.95	3.06
ΔAGB total (Mg ha^{-1} year $^{-1}$) change estimation by year								
Mean	0.057	0.30	1.22	0.42	−0.31	0.37	1.26	0.61
ΔAGB net (Mg ha^{-1} year $^{-1}$) change estimation								
n	11340296	2814599	941699	854782	418893	624610	418049	55842
Mean	0.56	0.56	2.18	0.77	0.75	0.86	1.83	

n= number of pixels at 25 × 25 m resolution, SD: Standard desviation, and CV: coefficient of variations.

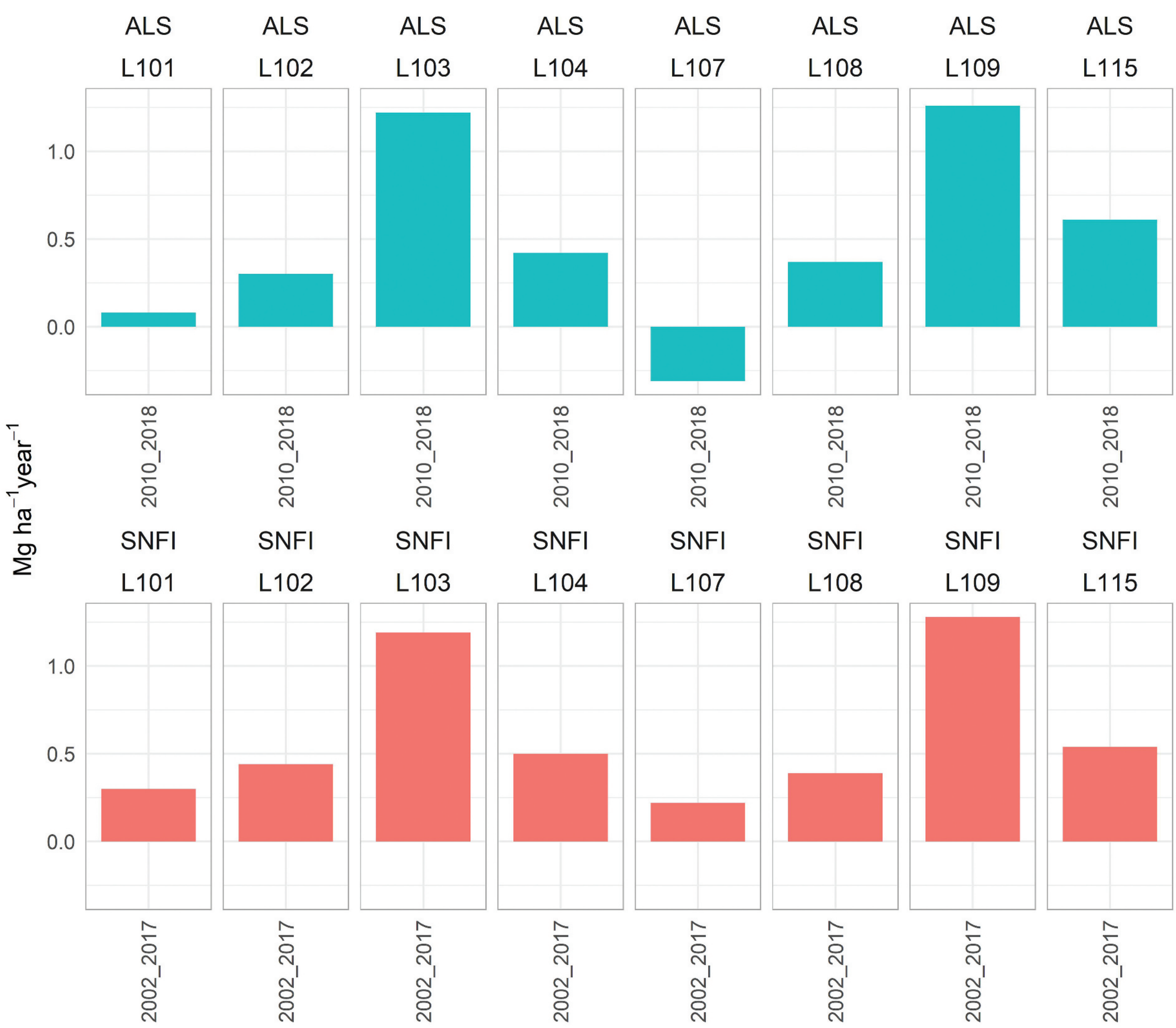

Figure 5a.

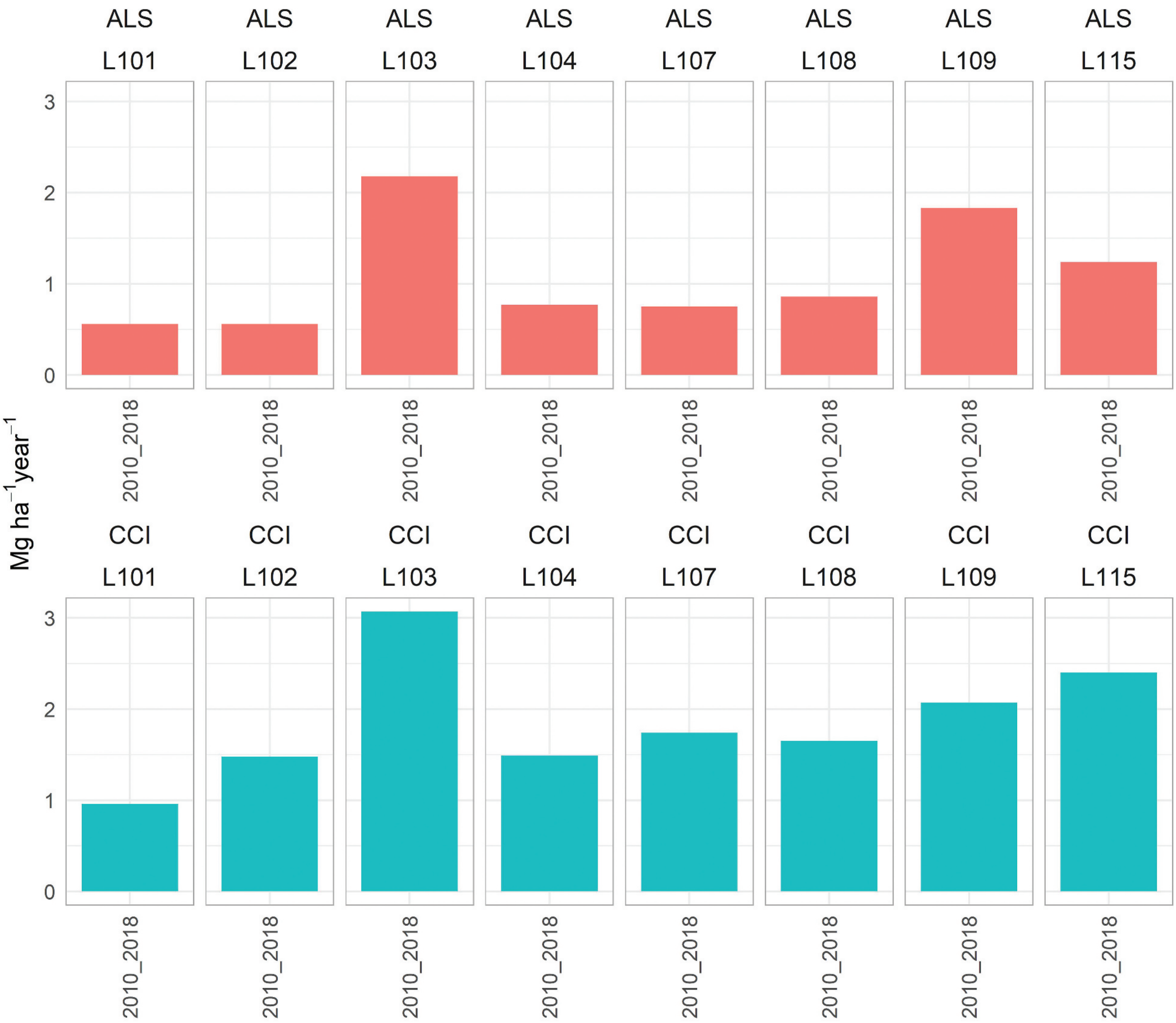

Figure 5b. The bar graphs of: (a) the mean of SNFI design-based and ALS estimated of ΔAGB total (mg ha^{-1} year $^{-1}$) change estimates and (b) ΔAGB net (mg ha^{-1} year $^{-1}$) change.

density) show the lowest growth (mean ΔAGB = 0.46 Mg ha^{-1}). Mixed forest of *Quercus ilex* (L104) and Mixed forest of conifers forest (L115), ΔAGB had a positive rate of AGB storage with mean values of 3.39 Mg ha^{-1} and 4.89 Mg ha^{-1}, respectively. Finally, the *Eucalyptus* spp. stands (L107) showed a negative rate of ΔAGB (ΔAGB = −2.53 Mg ha^{-1}) in the Region.

Comparison between AGB and ΔAGB-ALS and design-based SNFI estimates

The estimation of ΔAGB change estimates from design-based SNFI at regional level by strata (MITECO, 2020) were comparable by area and year with ΔAGB-ALS increments in terms of total and net changes. ΔAGB-ALS (Mg ha^{-1} year^{-1}) total change values (Figure 5(a)) were closed to the values obtained using SNFI at strata level, especially with similar AGB store growth rates in mature pine stands (1.22 Mg ha^{-1} year^{-1} for *P. pinaster* (L103) and 1.35 Mg ha^{-1} year^{-1} for *P Pinea* (L109) from ALS and 1.19 Mg ha^{-1} year^{-1} for L103 and 1.28 Mg ha^{-1} year^{-1} for L109 from design-based). However, the values varied in *Dehesas* (L101) (0.057 and 0.31 Mg ha^{-1} year^{-1} using ΔAGB-ALS and SFNI, respectively), in *Encinares* strata (0.30 and 0.44 Mg ha^{-1} year^{-1} using ALS-AGB based maps and SNFI, respectively), whereas *Eucalyptus* spp (L107) plantations showed a negative increment with mean value of ΔAGB-ALS = −0.31 Mg ha^{-1} year^{-1} and a positive increment mean ΔAGB-SNFI = 0.22 Mg ha^{-1} year^{-1} using ΔAGB-SNFI at strata level. In terms of ΔAGB (Mg ha^{-1} year^{-1}) net change considering the positive increment from both sources, the values were more similar from both sources (Figure 5(b)), except for the Mixed forest of conifers (L115) which showed a net ΔAGB value of 1.24 (Mg ha^{-1} year^{-1}) from ALS estimations and 2.28 (Mg ha^{-1} year^{-1}) from the SNFI based approach.

Comparison between AGB and ΔAGB-ALS based estimates and CCI Global AGB maps v3

In terms of mean values of AGB by formations (Table 4, Figure 6) for the year 2010 and 2018, CCI

Table 4. Summary of statistical analysis results for AGB in 2010, 2018 and their change estimation from each forest type using CCI global maps v3.

	AGB (Mg ha^{-1}) CCI estimation 2010							
	L101	L102	L103	L104	L107	L108	L109	L115
n	1323752	194823	56617	69134	57401	56656	490013	4209
Mean	5.34	14.51	53.77	23.64	20.27	24.51	40.02	65.02
SD	13.57	24.12	37.21	30.38	24.08	29.52	33.48	39.06
CV	2.54	1.66	0.69	1.29	1.19	1.20	0.84	0.60
AGB(Mg ha^{-1}) CCI estimation 2018								
Mean	3.12	12.26	60.23	22.72	17.99	23.23	37.50	61.88
SD	9.72	21.84	29.26	28.84	21.24	28.03	28.36	34.33
CV	3.12	1.78	0.49	1.27	1.18	1.21	0.76	0.55
ΔAGB (Mg ha^{-1}) CCI change estimation								
Mean	−2.22	−2.25	6.47	−0.92	−2.28	−1.28	−2.53	−3.14
SD	8.57	13.62	27.10	15.40	18.16	15.76	20.90	27.41
CV	−3.85	−6.06	4.19	−16.67	−7.95	−12.36	−8.26	−8.72
ΔAGB total (Mg ha^{-1} year $^{-1}$) change estimation by year								
Mean	−0.28	−0.28	0.81	−0.12	−0.29	−0.16	−0.32	−0.39

n= number of pixels at 100 × 100 m resolution, SD: Standard desviation, and CV: coefficient of variations.

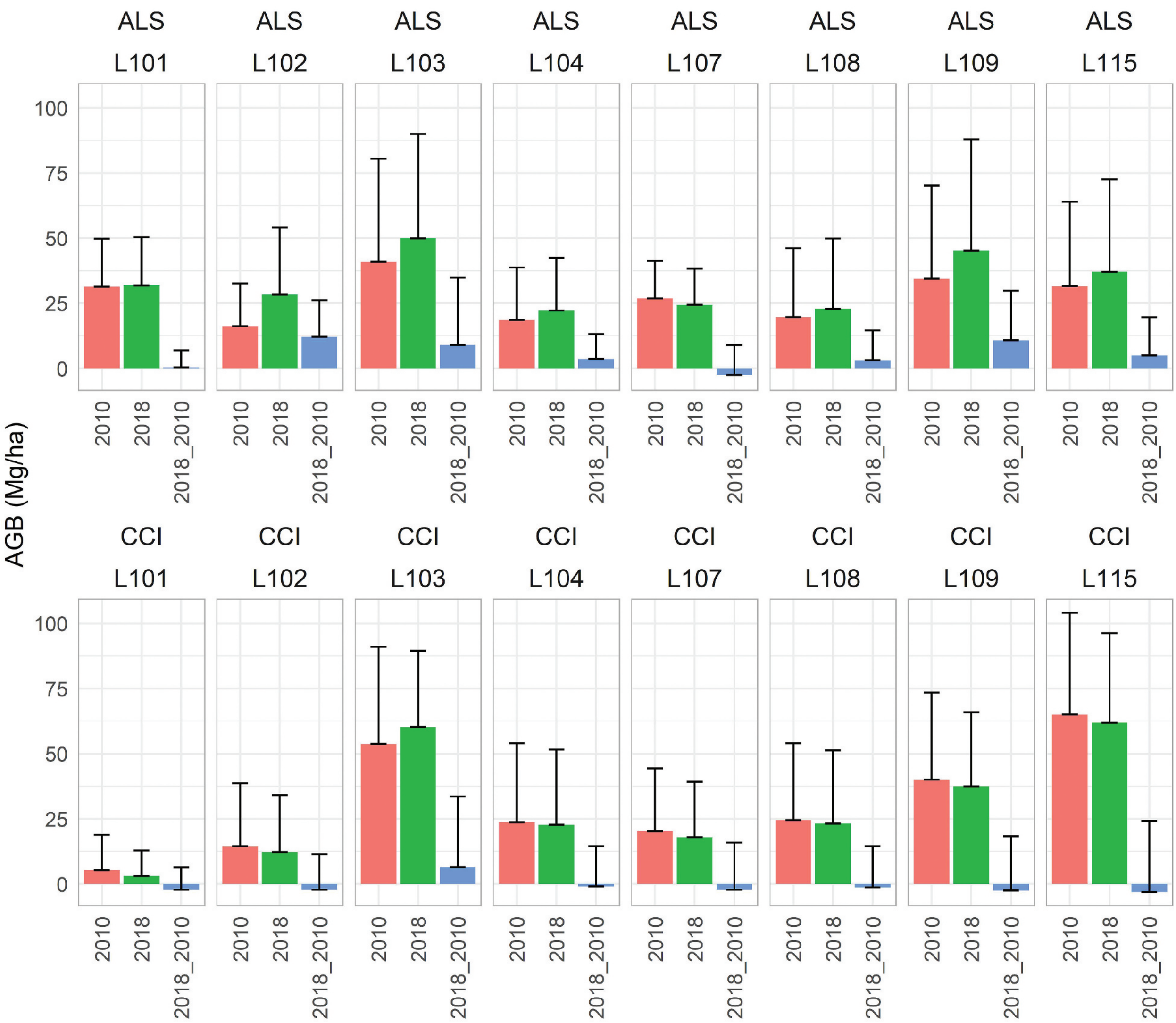

Figure 6. The bar graphs of the mean of ALS and CCI estimated AGB for each forest type in 2010, 2018 and their ΔAGB total (mg ha−1) change estimates. The standard deviation (SD) of the estimated AGB is showed by the error bars.

Biomass v3 products tended to underestimate the AGB for *Encinares* (L102), *Eucalyptus* spp (L107), *P. pinea* (L109) and specially in *Dehesas* (L101) which mean value was too strongly biased from the mean values of AGB from SNFI and ALS-AGB for this formation. CCI Biomass v3 for the year 2010 and 2018 tended to underestimate AGB comparing with SNFI strata and ALS-AGB maps in the most important strata in the Region. In the case of *P.pinaster* (L103) and Mixed forest of *Q,ilex* (L1014), CCI

Biomass v3 for the year 2010 and 2018 tended to overestimate AGB comparing with SNFI strata and ALS-AGB maps. Gains in AGB over the eight-year period between 2010 and 2018 could not be detectable in the region for all the formations, excepting for *P. pinaster* strata with positive values of 6.47 Mg ha^{-1}.

Comparison of the AGB estimated from ALS and the 2010 and 2018 CCI Biomass v3 products indicated that the histograms of v3 products differ noticeably with the 2010 and 2018 v3 (Figure 7), which showed also ΔAGB cannot be explained by changes in AGB in 8 years in Mediterranean forest with mean negative values for all the formations during the period, except for Mediterranean *P.pinaster* formation.

Overall, the distributions of the CCI products show discrepancy with the ALS -AGB map distribution of sparse old-growth oak forests (*Quercus* spp.): a) underestimation of AGB between 25 and 75 Mg ha^{-1}. b) overestimation of the distribution at lower values than 25 Mg ha^{-1}of AGB c) change in distribution from 2010 to 2018 cannot be explained by changes in AGB in 8 years in this type of forest. On the other hand, the best fit with the ALS-AGB map distribution was for the *Encinares* formations (^{L}102), *Alcornocales* (L108) and Mixed forest of *Quercus ilex* (104) but CCI showed a underestimation for areas (AGB <25 Mg ha^{-1}) and peaks of the distribution at 50–100 Mg ha^{-1} interval. In general, this peaks also appeared in *Pinus* spp. formations (L103 and L109. Negative increment ΔAGB total changes (Mg ha^{-1}) using the differences between CCI from 2010 to 2018 was found from young plantation from *Encinares* strata (L102) in areas with positive increment of ΔAGB-ALS (Mg ha^{-1} year^{-1}) during the period 2010–2018 (Figure 8). Figure 9 shows some examples of ΔAGB total (Mg ha^{-1}) change estimates in *Dehesas* (L101), *Pinaster* (L103) and Eucalyptus (L107) formation using ΔAGB -CCI v3 and ΔAGB – ALS-based maps.

Discussion

This study showed the utility of multitemporal-countrywide ALS measurements in Spain for monitoring of large-scale AGB dynamics in Mediterranean forest. To our knowledge this is one of the first study that systematically analyses, over a wide range of Mediterranean forest, the possibilities and limitations of the AGB-ALS-model-based estimations maps, CCI biomass maps and SNFI-design based time series estimations at regional scale to achieve the objective of estimating forest AGB-sequestration capacity

Our results were promising at regional scale and for a specific period of time using bi-temporal ALS-based maps. The ALS estimates of ΔAGB indicates that, in general, most of the forest type showed an overall gain in biomass. In fact, and when considering all the forest types, it was observed a mean ΔAGB of 1.37 Mg/ha revealing a positive balance in terms of biomass production at regional scale. The currently available ALS and SNFI data indicated that carbon sequestration continues in old sparse *Quercus*-spp forest that are centuries old. These results contradict the carbon neutrality theory of old-growth forest but confirmed the low carbon sequestration capacity in most sparse old-growth oak woodlands of *Quercus* species (e.g. Spanish *Dehesas* and Portuguese *Montados*) (Jiang et al., 2020; Luyssaert et al., 2008) during this period using ALS-based estimates. In this respect, the over pasture, the lack of natural regeneration, the holm oak decline (caused by root rot oomycetes, mainly *Phytophthora cinnamomi* Rands.) and the negative effects of climate change (Gea-Izquierdo et al., 2013), causes important losses in stand biomass stock due to the death of large and senescent trees, which represents a huge carbon pools (Büntgen et al., 2019), independently of the degree of naturalness (Molina-Valero et al., 2021). In contrast, the presence of middle-age oak forest and young stands of *Quercus* spp is more representative in *Encinares* strata (L102). They were noticeable carbon sink due to the creation of new reforestations and natural regeneration presented for *Encinares* (*Quercus ilex*) and Alcornocales (*Quercus suber*) strata. Approximately 70,000 ha of new reforestations of *Quercus ilex*, *Quercus suber* and mixed of *Quercus ilex* and *suber* have been implemented in the Region since 1999 in the framework of the EU forest strategy (Sequeda, 2017). The obtained results confirmed higher biomass stocks can be reached at earlier stages (Schall et al., 2018). On the other hand, the magnitude in the differences of AGB stocks suggested a revision of protocols to estimate AGB-carbon stocks and changes, especially in sparse tree-based oak woodlands of *Quercus* species. Our result demonstrated the magnitude and spatial distribution of AGB and carbon stocks could be improved using individual tree-based approach (ITC) in these sparse tree-based systems where multitemporal countrywide ALS data is available (Hyyppä et al., 2008). Promising results have been already obtained using ITC delineation algorithms in the Region using ALS point clouds (1–2 points m^{-2}) as an alternative to area based approach (ABA) in this strata (Guerra-Hernandez & Jurado-Varela, 2022).

Regarding the comparative analysis using increment of design-based estimations of ΔAGB total and net changes at strata level using SNFI3 and SNFI4 plots and ΔAGB total changes estimated from ALS, we found similar increments in *Pinus* spp (L103 and L109) and mixed forest formations (L115) from both methods. However, we noted some discrepancies specially in *Eucalyptus* spp and *Dehesas* formations. Although SNFI design-based and ALS model-based estimates and estimators for their variances are based on different theoretical principles and assumptions and, as consequence, they are not directly comparable

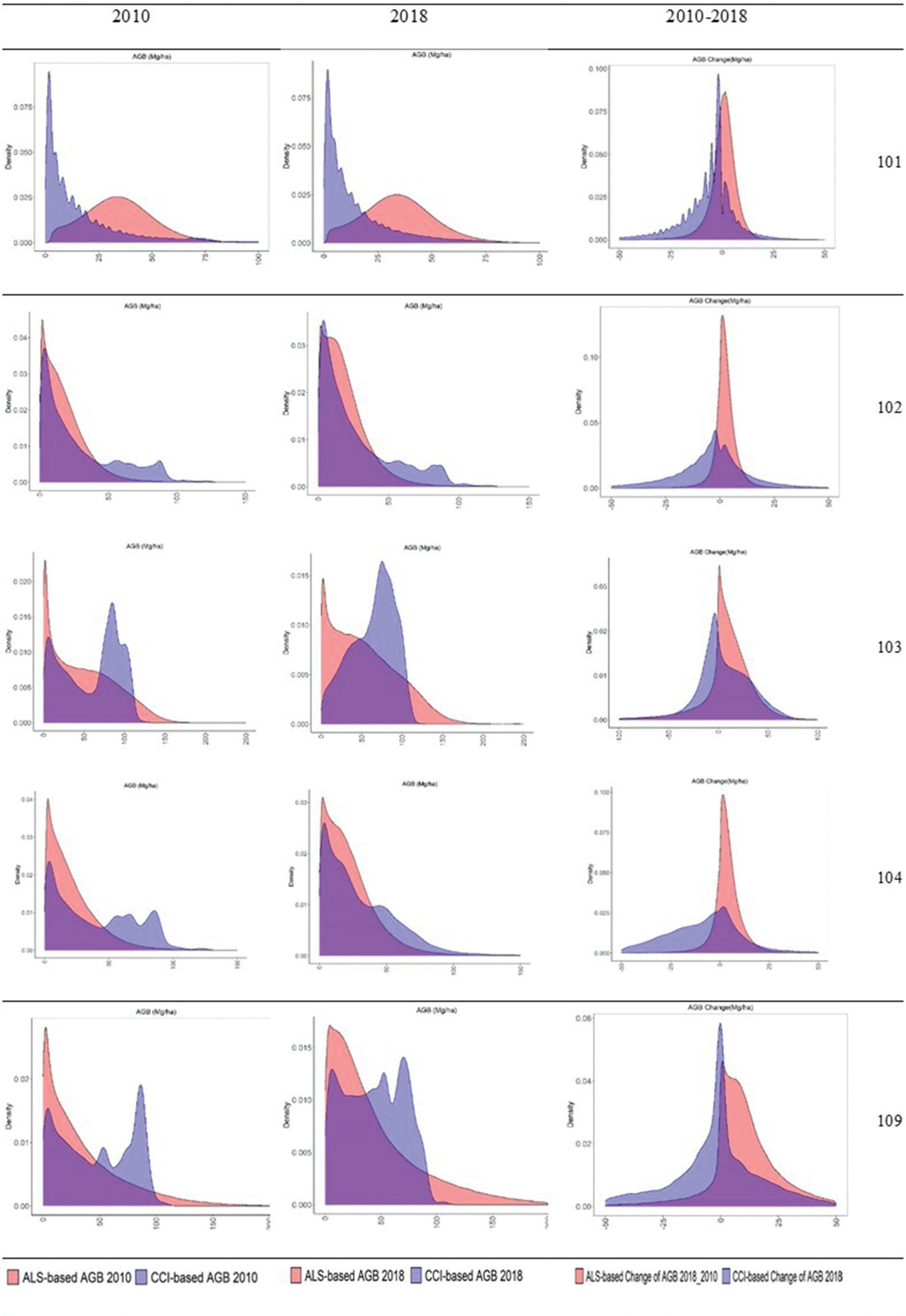

Figure 7. Frequency distributions of AGB derived over Extremadura region from ALS for 2010, 2018 and their changes ΔAGB (pink). GlobBiomass estimated AGB, 2010 CCI AGB v3, 2018 CCI AGB v3 and their changes by forest type (blue).

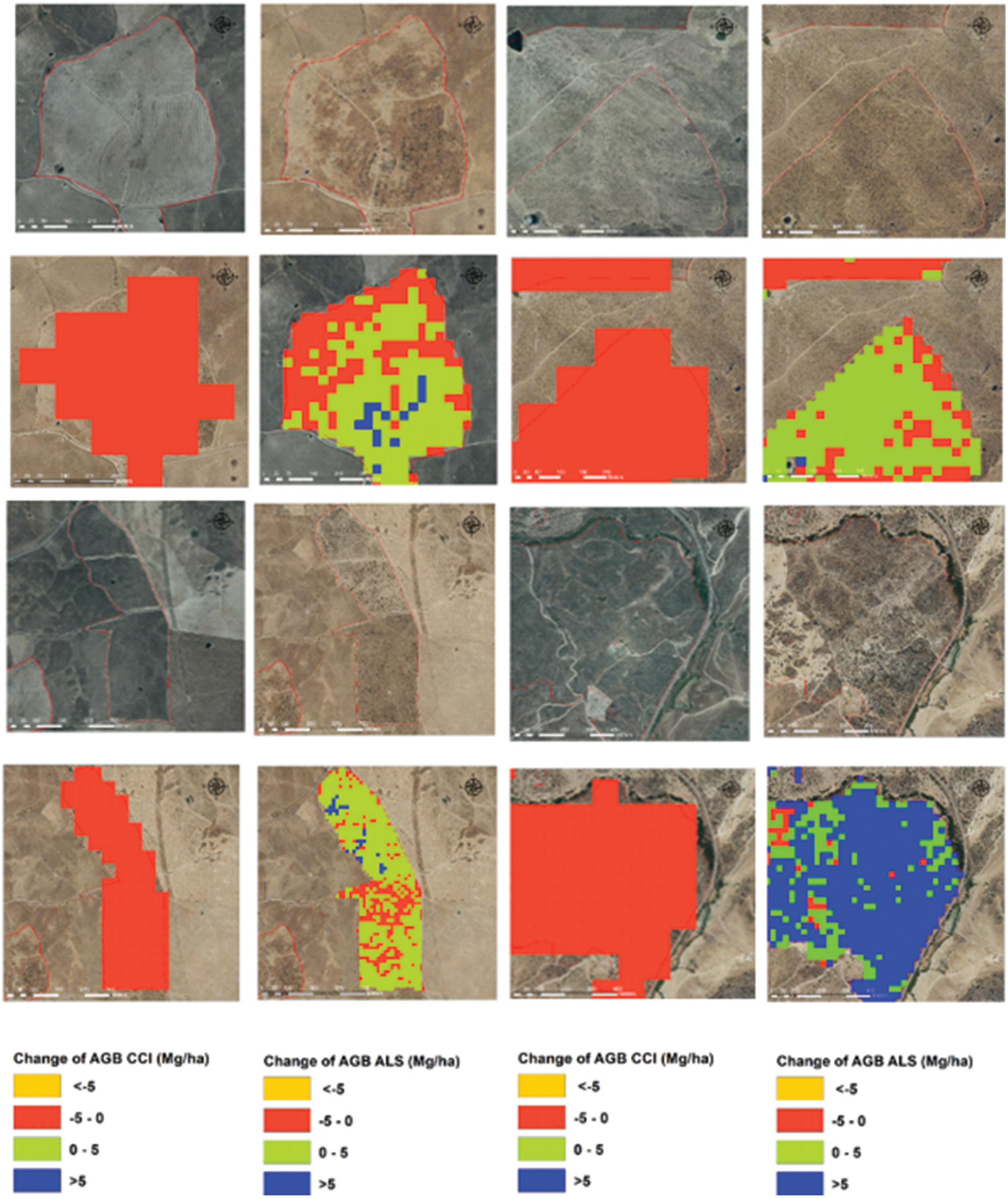

Figure 8. The spatial prediction of ΔAGB changes (between 2010 (left) and 2018 (right) represented by historical orthomosaics from PNOA project). Some highlighted locations of ΔAGB total (Mg ha^{-1}) change estimates in *Quercus ilex* young plantation from Encinares strata (L102) using ΔAGB -CCI v3 (left) and ΔAGB –ALS-based maps (right).

(McRoberts et al., 2022), this kind of comparisons were done in previous studies (Guerra-Hernández, Botequim, et al., 2022; McRoberts, 2006). One of the reasons to compare design-based and model-based estimates is that, if probability sample for design-based approach is adequately selected and model for model-based approach is correctly formulated, then both estimates should be relatively close (McRoberts, 2006). In the case of Eucalyptus plantation, design-based estimations from SNFI permanent plot were not efficient to the amount of fellings since more than 30,000 ha of *Eucalyptus* spp plantations have been removed in the region using Spanish Forest Map (SFM) associated and both inventories SNFI-3-4 in Extremadura. It is uncertain whether it will be possible to obtain unbiased estimates from temporary instead of

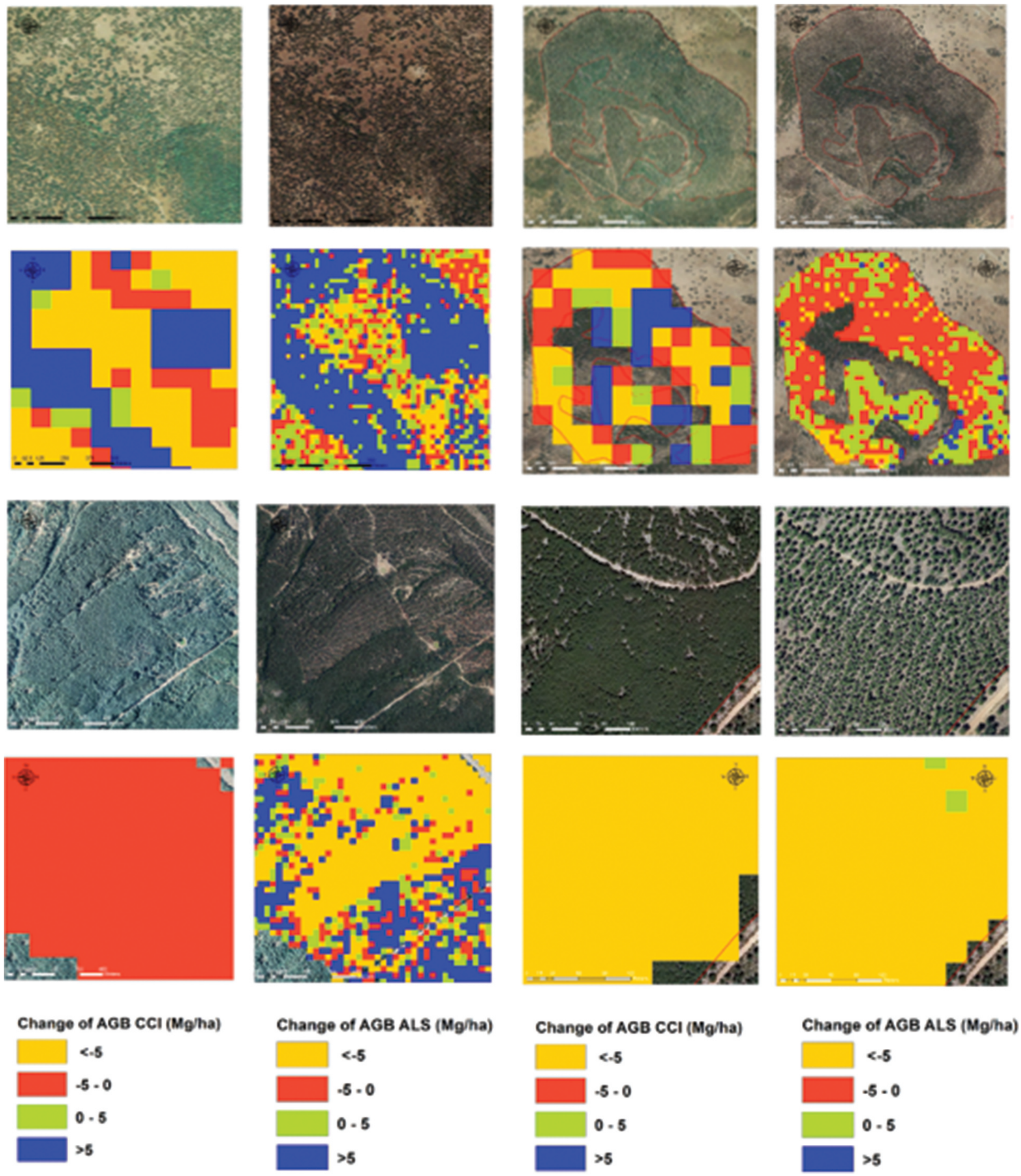

Figure 9. The spatial prediction of the changes of AGB across the research site (between 2010 (left) and 2018 (right) represented by historical orthomosaics from PNOA project). Some highlighted locations of ΔAGB total (Mg ha^{-1}) change estimates in Dehesas (L101), Pinaster (L103) and Eucalyptus (L107) formation using ΔAGB -CCI v3 (left) and ΔAGB –ALS-based maps (right).

permanent plots but the efficiencies of SNFI could be increased producing AGB-ALS model based maps that can be used for purposes such as calculating changes in AGB for more intensive forest management for this forest type. Existing NFI sample designs might be inadequate for estimating changes in intensive forest types such as the case of *Eucalyptus* spp, which thus increases uncertainties in estimating AGB changes for specific activities (Espejo et al., 2020). Recent studies already demonstrated that AGB-ALS based models currently enhances SNFIs in the region increasing the precision of large area inventory estimates providing inventory estimates with acceptable bias and less error for small areas for which sufficient field data are not available (Guerra-Hernández, Botequim, et al., 2022). In addition, maps based on both ALS and field data could be used to simulate NFI sampling designs in order to compare their efficiencies (Lister et al., 2020;

McRoberts & Tomppo, 2007). The lack of enough SNFI plots from design-based could explain the difference in *Eucalyptus* spp between both methods. On the other hand, the ΔAGB total changes by year derived from ALS underestimated the growth rate from design-based SNFI in L101 formation, probably due to the presence of more old sparse mature stands of *Quercus*-spp forest in *Dehesas* strata (L101), which presents a slow rate in terms of AGB increase. The criteria to classify these strata from SNFI could explain this difference since is based only in the canopy cover and the presence or not of agrosilvopastoral activity without considering the stand age which defined each formation. Increased sample sizes, changes in the criteria to classify the strata and/or integration of individual tree crown (ITC) approach using remotely sensed data may be required to estimate stock-difference correctly. The results confirmed that model-assisted method integrating field and remote sensing data could be also an alternative to compare changes estimates in aboveground carbon dynamics in this forest type. On the other hand, the impact of uncertainties in field reference data must be included in the future required international reporting (Persson et al., 2022).

The comparative analysis using CCI Global AGB maps v3 revealed that the AGB mean values from 2010 and 2018 were quite far from AGB estimation by unit of area using SNFI design-based inference and model-based ALS-AGB maps, especially in *Dehesas* and *Encinares* formations. AGB CCI- (AGB) retrievals values for 2010 and 2018 are highly underestimated in most of the forests and slightly overestimated for *P.pinaster* (L103) and Mixed forest of *Quercus ilex* strata (L104). Our results reflected the difficulty in estimating ΔAGB in circumstances where the growth rate of ΔAGB is small which needs very accurate estimations to enable for estimating the change with enough confidence. CCI Global AGB maps v3 2010 and 2018 and their ΔAGB increment could not estimate the ΔAGB accurately in Mediterranean environments. In our study, the small estimated ΔAGB-magnitude could be due to slow growth rate of old sparse *Quercus*-spp forest and an active forest management for timber production in the case of *Pinus* spp species in the region. According to the objectives of regional forest planning strategies to eliminate the *Eucalyptu*s spp. specie, the result confirmed the continuous removals of these stands during the period of 2010–2018 in the Region. The results confirmed that absolute difference in maps of CCI AGB 2018 and 2010 has several limitations, probably reflecting the lack of sufficient field data and LiDAR data needed to generate the CCI AGB maps (Santoro & Cartus, 2021). The comparison of the histograms of AGB of the Extremadura region from the CCI Biomass products and ALS product (Figures 8 and 9) highlights differences with bimodal distribution in the AGB associated with woodlands from CCI and unimodal distribution from ALS. AGB change histograms from CCI product also revealed some peaks in the distribution. Different datasets and data density (number of EO data) were used to generate the AGB maps of 2010 and 2018 could explain the limitations of global AGB maps and usability for verifying AGB dynamics at Regional scale in this type of forest. Our study highlighted the need to further refine AGB Global products to estimate changes in biomass carbon stocks. Future versions of CCI product could be enhanced by the upcoming NASA-ISRO Synthetic Aperture Radar (NISAR) satellite mission in 2024 that will provide denser L-band time series data at a higher spatial (10 m) and temporal resolution (12 days) (Khati et al., 2021), and the increasing amount of spaceborne-LiDAR data from GEDI and ICESat-2 mission in the next years. The increasing availability and update of NFIs create new chances for synergizing with space-based data at the national level (Karimon et al., 2022; Labrière et al., 2022). NFI projects and ALS-based AGB available at national level might be used to further refinement and specific AGB model calibration for the CCI product.

Conclusions

The results of our study demonstrate that multi-temporal ALS-based maps are expected to be suitable for estimating AGB change in Mediterranean forest. Bi-temporal ALS data coupled with field reference data deal a great method for calculating pools and changes in aboveground carbon dynamics in Mediterranean areas. On the contrary, this study revealed that CCI-AGB based change could not be explained using Global-AGB for 2010 and 2018, given the low growth rates in the region for most of the *Quercus* spp. formations, and specially for open old-oak woodlands of *Quercus* species. The CCI-AGB based change was not capable of supporting quantification of biomass change. For future studies, it seems more suitable to use ITC approach in sparse tree-based forest ecosystems and the need to harmonize both ALS countrywide and NFI field-AGB data to enhance their usage at country level.

Acknowledgments

We acknowledge Vicente Sandoval and Elena Robla from National Forest Inventory Department. a research grant funded by the Foundation for Science and Technology (FCT), Portugal to Dr. Guerra (#CEECIND/02576/2022). We thank the Spanish National Forest Inventory (SNFI) from MAPA for making the ground data of the 3th (SNFI-3) and 4th round (SNFI-4) available to us to conduct the study.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data that support the findings of this study are available from the corresponding authors, Juan Guerra Hernandez, Alfonso Jurado-Varela and Vicente Sandoval-Altelarrea, upon reasonable request.

Author contributions

Conceptualization, JGH, AP, VS; methodology, JGH, FTS, SG; BB, AJV, VS, software JGH, AP, FTS; data curation, JGH, FTS, SG; BB, AJV, VS; model validation, JGH, FTS, SG; BB, AJV,VS; investigation, JGH, FTS, SG; BB, AJV,VS; writing – original draft preparation, JGH, FTS, SG; BB, AJV, VS; writing – review and editing, JGH, FTS, SG; BB, AJV, VS; visualization, JGH, FTS, SG; BB, AJV,VS; supervision, SSP, AM; project administration, JGH, AP,AJV, VS; and funding acquisition, JGH, AP, AJV,VS.

Funding

The authors also thank to Forest Research Centre, a research unit funded by Fundação para a Ciência e aTecnologia I.P. (FCT), Portugal (UIDB/00239/2023). This research was supported by the project "Extensión del cuarto inventario forestal nacional mediante técnicas LiDAR para la gestión sostenible de los montes de Extremadura" from the Extremadura Forest Service (FEADER nº 1952SE1FR435) and research grant funded by the Foundation for Science and Technology (FCT), Portugal to Dr. Guerra- Hernández (#CEECIND/02576/2022). Project "Apoio à Contratação de Recursos Humanos Altamente Qualificados" (NORTE-06-3559-FSE-000045). under the PORTUGAL 2020 Partnership Agreement. ForestWISE - Collaborative Laboratory for Integrated Forest & Fire Management, was recognized as a CoLAB by the Fundação para a Ciência e a Tecnologia, I.P. (FCT).

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