AIT Series

Trends in earth observation

Volume 2

Planet Care from Space

Edited by Dessena M.A., Melis M.T and Rossi P.

Planet Care from Space

Edited by

Maria Antonietta Dessena, Maria Teresa Melis and Patrizia Rossi

AIT Series: Trends in earth observation

Volume 2 - Published in September 2021
Edited by Maria Antonietta Dessena, Maria Teresa Melis and Patrizia Rossi
Published on behalf of the Associazione Italiana di Telerilevamento (AIT)
Via Lucca 50
50142 Firenze, Italy

ISSN 2612-7148
ISBN 978-88-944687-0-0
DOI: 10.978.88944687/00

All contributions published in the Volume "Planet Care from Space" were subject to blind peer review from independent reviewers.

Publication Ethics and Publication Malpractice Statement
Editors, Reviewers and Authors agreed with Publication Ethics and Publication Malpractice Statement

Multitemporal LiDAR data for forest carbon monitoring in Mediterranean Forest

G. D'Amico[1]*, F. Giannetti[1], E. Vangi[1,2], C. Borghi[1], S. Francini[1,2,3], D. Travaglini[1], G. Chirici[1]

[1] Dipartimento di Scienze e Tecnologie Agrarie, Alimentari, Ambientali e Forestali, Università degli Studi di Firenze - (giovanni.damico, francesca.giannetti, elia.vangi, costanza.borghi, saverio.francini, davide.travaglini, gherardo.chirici)@unifi.it
[2] Dipartimento di Bioscienze e Territorio, Università degli Studi del Molise
[3] Dipartimento per la Innovazione nei sistemi Biologici, Agroalimentari e Forestali, Università degli Studi della Tuscia

KEY WORDS: LiDAR, growing stock volume, small-scale forest management, carbon sequestration.

ABSTRACT:

Forests are widely recognized as essential ecosystems for sequestering carbon and to mitigate the increase of atmospheric carbon dioxide, though could lose, or reduce this function under future climatic change. To maintain or improve carbon mitigation and to assess species adaptation to climate change small-scale forest monitoring is crucial, especially in Mediterranean forests where warmer and drier seasons are expected. Airborne Laser Scanner (ALS) data are efficiently used for defined carbon mapping, but few studies have used multi-temporal lidar surveys to evaluate carbon sequestration in Mediterranean forests.
This study focuses on the forested area of Monte Morello (Florence, Central Italy) which was surveyed by ALS in 2008 and 2015 with scan densities of 1.5 and 4.4 pulse/m^2, respectively. Herein, we compare the multitemporal ALS data with field forest inventory plots to estimate growing stock volume (GSV) and carbon sequestration in Mediterranean mixed broadleaved and coniferous forests. Independently of laser sampling rate we estimate, using an area-based approach, the forest GSVs and carbon sequestrations for 2008 and 2015 using random forests and a multiple linear regression model ($R^2 = 0.9$; RMSE% = 17%). Based on the multitemporal maps, we derived information related to (i) forest growth, (ii) forest species carbon sequestration, (iii) small-scale forest management. The entire study area increased sequestered carbon by 58%, mainly for coniferous mixed forests. Overall, our study describes a well-suited technique for multitemporal ALS analysis and highlighting the potential of the use of multitemporal ALS data to map forest resources for forest management activities.

1. INTRODUCTION

Forests supply a vast array of forest ecosystem services such as timber, recreation, landscape, they store carbon, and regulate the water cycle and climate (Eggleston et al., 2006, Vizzarri et al., 2015). In this context, Sustainable Forest Management (SFM) ensures the perpetuation of forest ecosystem services, but requires information on several forest variables that must be acquired to monitor the state of forest ecosystems and to plan specific forest management activities, especially in a climate change context. Nowadays, to monitor forest ecosystems, the use of spatially explicit forest variables derived integrating remote sensing data and field measures are considered essential to conduct site-specific sustainable forest management activities.
Among remote sensing technology, Light Detection And Ranging (LiDAR) data collected by Airplane or helicopter platforms (i.e., Airborne Laser Scanning, ALS), is considered the most useful technology to map forest ecosystems since from laser pulse it is possible to model and estimate the 3D structure of forests and to easily estimate biophysical forest variables (e.g. tree heights, vertical structure, growing stock volume, carbon stock) (Dubayah & Drake, 2000; Babcock et al., 2015). In fact, in the last decades, many studies demonstrated the utility of ALS to monitor forest resources (Nelson, 2013; Kangas et al., 2018). Given its proven capabilities in mapping forest variables, the use of ALS data is increasing rapidly worldwide (Zolkos et al., 2013), and many countries, such as Sweden, Finland, Denmark, invested in the wall-to-wall acquisition of ALS data to support forest inventory programs.
Increased availability of ALS data provides an opportunity to measure and study forest ecosystem dynamics over time (Dubayah et al., 2010). However, despite the potential of using multitemporal ALS data to support forest change monitoring, its implementation in small-scale sustainable forest management activities is still limited (Dassot et al., 2011).
Zhao et al. (2018), used four multitemporal ALS surveys in Scotland for monitoring forest carbon stock, while Cao et al. (2016), estimated forest biomass dynamics in subtropical forests. Some researchers underline that to use multitemporal ALS data efficiently many practical problems need to be overcome as the availability of ancillary ground data coherent with the multitemporal ALS acquisition, effects of variation in ALS sampling, and the analysis methods used to elaborate ALS data and to model forest variables (Næsset, 2009; Zhao et al., 2011). Most forest biophysical variables, such as biomass and carbon stock, can be estimated by ALS via correlative models, requiring paired forest inventory data for model calibration (Næsset et al., 2005).
This study aims to assess the utility of multitemporal ALS data for tracking forest and carbon dynamics in a Mediterranean study area. An emphasis is on evaluating and improving multitemporal ALS methods to measure forest changes over time at grid levels, including biomass change, and carbon stock. To do so we acquired two ALS data from surveys executed in 2008, and 2015, over a Mediterranean mixed broadleaf and coniferous forest. The ALS data were combined with field plots data acquired in 2014 and used to quantify forest changes at grid levels. We also estimated biomass and carbon stock over time, using ancillary data to calibrate ALS models.

2. MATERIALS

2.1 Study area

The study was carried out in Monte Morello, a forest area located near Florence's urban area in Central Italy (43°85' N, 11°23' E). Specifically, the study area corresponds to the overlapping forest area of two ALS surveys, for a total of 1465 ha. The area is characterized by a typical Mediterranean climate, with rainfall concentrated in spring and autumn and dry summer. Elevation ranges between 600 m and 700 m a.s.l. The dominant species are conifers (*Cupressus sempervirens* L., *Pinus nigra* Arn.) that originated from reforestation programmes of the last century, and oaks (*Quercus cerris* L., *Quercus ilex* L., *Quercus pubescens* L.) (Bottalico et al., 2017) (Fig. 1).

* Corresponding author

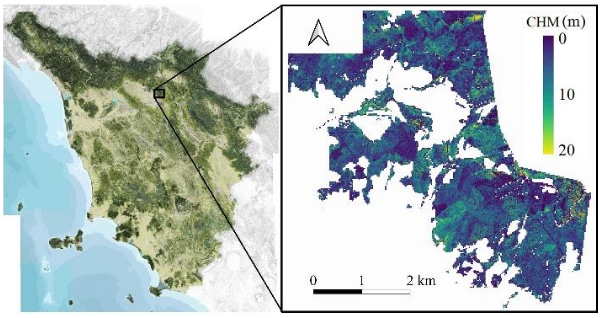

Figure 1. Study area.

2.2 Field plot data

Local forest inventories were carried out using a tessellated stratified sampling scheme (Barabesi and Franceschi, 2011) based on a 0.4 × 0.4 km grid. In each of the 41 grid units, a point was randomly selected among the forest area, constructing a sample of 41 points. A 13-m radius circular plot was established with a center at each sampling points. The plot coordinates were recorded using a GNSS receiver. Diameters at breast height (DBH, 1.30 m) were measured for all living trees with DBH ≥ 2.5 cm, for all callipered tree the height (H) was also recorded (Bottalico et al., 2017). In each field plot, the GSV was calculated by aggregating tree total GSV, estimated at tree level from species-specific allometric equations (Tabacchi et al., 2011).

2.3 Forest map

The CORINE Land Cover (CLC) project of the European Environment Agency, consists of a land cover map; it is based on a nomenclature system of 44 classes produced by photointerpretation of high-resolution satellite imagery. CLC uses a minimum mapping unit of 25 hectares. For this study, we acquired the CLC map for the reference year 2018, which for Italy provides an IV level of detail that can be assimilated to the forest types.

2.4 ALS data and processing

The first ALS survey available for the study area was carried out in winter 2008 with an ALS ALTM (Airborne Laser Terrain Mapper) Gemini sensor that operated at a flight height of 3000 m a.s.l. The sensor recorded two echoes per pulse with an average density of approximately 0.7 points/m^2. The second flight was carried out in May 2015 with a RIEGL LMS-Q680i laser scanner. The flying altitude was 1100 m above terrain level. Full-waveform ALS data were registered and discretized to a point density of 10 points/m^2. Standard pre-processing with LAStools (Isenburg, 2017) was used to remove noise in the ALS data and ALS echoes were classified as ground/non-ground. The relative heights above ground for echoes classified as non-ground were calculated and used to construct a canopy height model (CHM) with a spatial resolution of 1 m using the adaptive triangulated irregular network algorithm (Axelsson, 2000). For each plot, 54 echo-based and metrics were calculated (Hawryło et al., 2020) using the package *lidR* for R (Russell et al., 2020). The study area was tessellated into 23×23m pixels whose size mimicked the area of the field plots measured in the field. As for the field plots, 54 ALS metrics were calculated for each pixel.

3. METHODS

We combined ALS metrics and field data to derive forest variables for both ALS surveys, examining the temporal change. We used area-based ALS metrics at grid levels (23×23m coherent with field survey) as independent variables and field data as dependent variables to evaluate the accuracy of multiple modelling strategies and to estimate biomass and carbon dynamics.

3.1 GSV dynamics estimation

Carbon sequestration and its change were estimated from the GSV values predicted through regression models by relating field-based volume with ALS metrics.
We tried two model techniques (i) multiple linear regression model (MLR), and (ii) the random forests (RF) (Breiman et al., 2001). MLR techniques entail the use of model:

$$y_i = \beta_0 + \beta_1 x_{1i} + \ldots + \beta_p x_{pi} + \varepsilon_i \quad (1)$$

where i indexes sample units, y_i denotes the single response variable, p≥1 denotes the number of predictor variables, j =1, …, p indexes the predictor variables, βj is the respective regression coefficient, and ε_i denotes a random residual term assumed to be distributed N (0, σ_i^2). The model was optimized by comparing all possible combinations of all numbers of predictors with coefficients estimated using ordinary least squares.
RF is a decision tree algorithm and nowadays is among the most popular ensemble methods for classifying and predicting forest variables (Breiman, 2001). Its effectiveness is supported both empirically and theoretically, especially due to its reliance on not just one decision tree but an ensemble of trees as a strategy to improve model robustness. Specifically, RF uses a randomly chosen subset of predictors at each splitting node. RF was optimized by selecting the combination of predictor variables and parameter values (ntree and mtry) that minimized the root mean square error (RMSE) calculated using the leave-one-out (LOO) cross validation technique (McRoberts et al., 2015). The model fitting and optimization phase was performed using the *randomForest* package within R.
The most accurate models derived by MLS and RF were used to predict the GSV for all 23×23m grid cells of the study area to produce a 23×23m resolution GSV map for 2015. The same models were also used to predict the GSV using as predictor the 2008 ALS metrics. Negative GSV predictions were set to 0 in both years (Chirici et al., 2020). For each method, we calculated the coefficient of determination (R^2) between the measured and predicted values, the root mean square error (RMSE), the relative RMSE (RMSE%) and the mean absolute error (MAE).

$$RMSE = \sqrt{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 / n} \quad (2)$$

$$MAE = \sum_{i=1}^{n} |(\hat{y}_i - y_i)| / n \quad (3)$$

where $\hat{y}_i$ and y_i are respectively the predicted and ground reference values of GSV for the ith sample plot and n is the number of plots. The RMSE% were calculated as the percentage of the average ground reference value of GSV.

3.2 Carbon sequestration

For every CLC forest typology, starting from GSV estimation, the amount of aboveground forest biomass (t ha^{-1}) was estimated, for every forest typology, through the species-specific relationships presented in Federici et al. (2008). Finally, we calculated carbon sequestration, defined as the rate of change in forest carbon stock. Forest carbon stock was simply converted from aboveground biomass, derived by ALS metrics, using a generic scaling factor of 0.5 (Zhao et al., 2018); therefore, carbon sequestration was obtained as the change in total tree biomass in each pixel per year, scaled by 0.5. Positive values of carbon sequestration indicated sinks associated with carbon accumulation from natural growth, while negative were carbon sources due to various disturbances.

4. RESULTS

Both imputation methods produced comparable results with only limited differences. Independently of the parameter used for evaluating the results, RF achieved the greatest accuracy. R^2 ranged between 0.89 and 0.91; RMSE between 38.3 m^3 ha^{-1} and 38.7 m^3 ha^{-1}; and RMSE% between 17.0% and 17.1% (Fig 2).

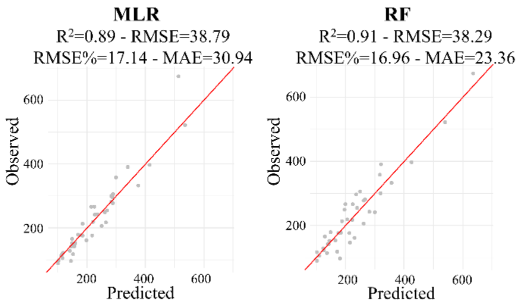

Figure 2. Scatterplots of GSV observations versus predictions for both the imputation approaches. R^2, RMSE, RMSE%, and MAE are based on LOO-CV during the optimization phase.

Of the 54 available predictors considered during the optimization phase, only 10 variables were selected by both the models. In terms of the usefulness of the predictors, the percentile values of point height variables were the most frequently selected, zq20, zq45 and zq75 for the MLS model and, zq70, zq75, zq85, qz90, zq95 for RF. In both the models the standard deviation of point heights (zsd) and the 75 percentile values of point heights were also selected. The other variables that were selected at least once were the maximum value of point heights (zmax) and the cumulative percentage of returns from the second height layers, considering the height measures divided into 10 equal intervals (zcum2). RF optimization involved 300 regression trees.
Considering these limited differences in models results the easier MLR model was selected for the following estimation phase. The MLR model was used to predict GSV for each one of the 27,701 23×23m resolution forest grid cells in the study area. GSV predictions ranged between 0 and 598m^3 ha^{-1} with a standard deviation of 98.0 m^3 ha^{-1} for 2015, while in 2008, GSV predictions ranged between 0 and 588m^3 ha^{-1} with a standard deviation of 90.7 m^3 ha^{-1}.

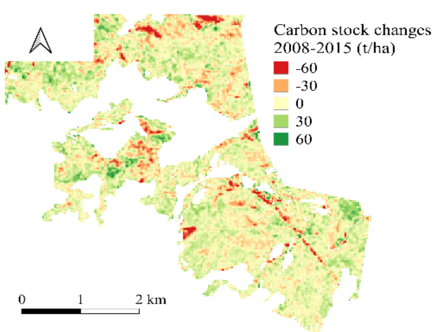

Figure 3. Dynamics in carbon storage over the study period.

The estimated aboveground forest biomass in the grid cells had values that ranged between 0 and 550 t ha^{-1} with a standard deviation of 73 t ha^{-1} for 2008 and between 0 and 574 t ha^{-1} with a standard deviation of 68 t ha^{-1} for 2015. Next, forest carbon stock maps were derived for both years. The carbon stored between the two surveys was in total 15195 t, while the carbon sources due to various disturbances were 11539 t, for net sink of 3656 t (Fig. 3).

5. DISCUSSION

In our work we used data from two ALS surveys, to estimate the stored forest carbon and its dynamics in a study area in central Italy. We observed an increase in total carbon storage of 58%, mainly for coniferous mixed forests with 2133 t sequestered (3.54 t ha^{-1}; 0.44 t ha^{-1} y^{-1}). On the other hand, most of the losses were mainly in broadleaves mixed forests with 590 t lost (1.62 t ha^{-1}; 0.20 t ha^{-1} y^{-1}).
The results we achieved demonstrate the usefulness of multitemporal ALS data to monitor forest GSV and carbon stock changes, which is crucial to support sustainable forest management, conservation in the Mediterranean area. Although RF was found to be the most accurate method, only small differences in prediction accuracies were found with the multiple linear regression (Chirici et al., 2020).
Despite the potential usefulness of ALS data to support sustainable forest management is well documented by a vast number of studies, a wall-to-wall ALS coverage in Italy is not available yet (59% of Italian forests) and only a very limited portion of forests are covered by multitemporal data (33% of Italian forests) (D'Amico et al., 2021). This limit the application of the methodology we presented in this contribution over large areas. Moreover, for our study, the lack of field data collected close in time to the first ALS survey, can be considered a limiting factor in verifying the effectiveness of the 2008 GSV estimation (Næsset et al., 2005). However, we demonstrated that also in Mediterranean forests, where more changes are expected due to climate change effects (Ogaya & Peñuelas, 2021), the use of multitemporal ALS data can be considered as the best way to spatially estimate forest dynamics.

6. CONCLUSION

Two main conclusions can be drawn from this work. Firstly, ALS data are confirmed as a reliable and efficient source of information for modeling carbon stock, even in complex Mediterranean forest areas. Secondly, the capability of ALS data to accurately predict forest carbon storage allows the use of simple parametric models, indeed both the tested modeling approaches predicted GSV with comparable results.
Overall, for ecological and environmental monitoring, the use of ALS data is expected to be further increased. The role of LiDAR technology (from aerial or terrestrial surveys) will be even more essential in supporting research and management activities, such as those related to carbon science forest degradation, biodiversity conservation, and land use. Under this point of view, Italy is still waiting for a complete ALS wall-to-wall coverage, that will have to be updated regularly to facilitate the prediction of forest variables and their trends in space and time with greater accuracy (Chirici et al., 2020).

7. REFERENCES

Axelsson, P., 2000. DEM generation from laser scanner data using adaptive TIN models. Int. Arch. Photogramm. Remote. Sens. 33, 111–118.

Babcock, C., Finley, A.O., Bradford, J. B., Kolka, R., Birdsey, R., Ryan, M.G., 2015. LiDAR based prediction of forest biomass using hierarchical models with spatially varying coefficients.

Remote Sensing of Environment, 169, 113-127. https://doi.org/10.1016/j.rse.2015.07.028

Barabesi, L., Franceschi, S., 2011. Sampling properties of spatial total estimators under tessellation stratified designs. Environmetrics 22, 271–278. https://doi.org/10.1002/env.1046

Bottalico, F., Chirici, G., Giannini, R., Mele, S., Mura, M., Puxeddu, M., McRoberts, R.E., Valbuena, R., Travaglini, D., 2017. Modeling Mediterranean forest structure using airborne laser scanning data. Int. J. Appl. Earth Obs. Geoinf. 57, 145–153. https://doi.org/10.1016/j.jag.2016.12.013

Breiman, L. Random Forests. Machine Learning 45, 5–32 (2001). https://doi.org/10.1023/A:1010933404324

Cao, L., Coops, N.C., Innes, J.L., Sheppard, S.R., Fu, L., Ruan, H., She, G., 2016. Estimation of forest biomass dynamics in subtropical forests using multi-temporal airborne LiDAR data. Remote Sens. Environ. 178, 158–171. https://doi.org/10.1016/j.rse.2016.03.012

Chirici, G., Giannetti, F., McRoberts, R.E., Travaglini, D., Pecchi, M., Maselli, F., Chiesi, M., Corona, P., 2020. Wall-to-wall spatial prediction of growing stock volume based on Italian National Forest Inventory plots and remotely sensed data. Int. J. Appl. Earth Obs. Geoinf., 84, 101959. https://doi.org/10.1016/j.jag.2019.101959

D'Amico, G., Vangi, E., Francini, S., Giannetti, F., Nicolaci, A., Travaglini, D., Massai, L., Giambastiani, Y., Terranova, C., Chirici, G., 2021. Are we ready for a National Forest Information System? State of the art of forest maps and airborne laser scanning data availability in Italy. iForest 14: 144-154. https://doi.org/10.3832/ifor3648-014

Dassot, M., Constant, T., Fournier, M., 2011. The use of terrestrial LiDAR technology in forest science: application fields, benefits and challenges. Ann. For. Sci. 68, 959–974. https://doi.org/10.1007/s13595-011-0102-2

Dubayah, R.O., Drake, J.B., 2000. Lidar remote sensing for forestry. Journal of forestry 98.6 (2000): 44-46. https://doi.org/10.1093/jof/98.6.44

Eggleston, S., Buendia, L., Miwa, K., Ngara, T., Tanabe, K., 2006. IPCC guidelines for national greenhouse gas inventories. Institute for Global Environmental Strategies Hayama, Japan.

Federici, S., Vitullo, M., Tulipano, S., De Lauretis, R., Seufert, G., 2008. An approach to estimate carbon stocks change in forest carbon pools under the UNFCCC: the Italian case. iForest 1: 86-95. https://doi.org/10.3832/ifor0457-0010086

Hawryło, P., Francini, S., Chirici, G., Giannetti, F., Parkitna, K., Krok, G., Mitelsztedt, K., Lisanczuk, M., Sterenczak, K., Ciesielski, M., Wezyk, P., Socha, J., 2020. The Use of Remotely Sensed Data and Polish NFI Plots for Prediction of Growing Stock Volume Using Different Predictive Methods. Remote Sens., 12(20), 3331. https://doi.org/10.3390/rs12203331

Isenburg, M., 2017. LAStools - efficient LiDAR processing software, from http://rapidlasso.com/LAStools.

Kangas, A., Astrup, R., Breidenbach, J., Fridman, J., Gobakken, T., Korhonen, K.T., Maltamo, M., Nilsson, M., Nord-Larsen, T., Næsset E., Olsson H., 2018. Remote sensing and forest inventories in Nordic countries – roadmap for the future, Scandinavian Journal of Forest Research, 33:4, 397-412. https://doi.org/10.1080/02827581.2017.1416666

McRoberts, R.E.; Næsset, E.; Gobakken, T., 2015. Optimizing the k-Nearest Neighbors technique for estimating forest aboveground biomass using airborne laser scanning data. Remote Sens. Environ., 163, 13–22. https://doi.org/10.1016/j.rse.2015.02.026

Næsset, E., 2009. Effects of different sensors, flying altitudes, and pulse repetition frequencies on forest canopy metrics and biophysical stand properties derived from small-footprint airborne laser data. Remote Sens. Environ. 113, 148–159. https://doi.org/10.1016/j.rse.2008.09.001

Næsset, E., Bollandsås, O.M., Gobakken, T., 2005. Comparing regression methods in estimation of biophysical properties of forest stands from two different inventories using laser scanner data. Remote Sens. Environ. 94, 541–553. https://doi.org/10.1016/j.rse.2004.11.010

Nelson, R., 2013. How did we get here? An early history of forestry lidar1. Can. J. Remote. Sens. 39, S6–S17. https://doi.org/10.5589/m13-011

Ogaya, R., Peñuelas, J., 2021. Climate Change Effects in a Mediterranean Forest Following 21 Consecutive Years of Experimental Drought. Forests, 12, 306. https://doi.org/10.3390/f12030306

Roussel, J.R., Caspersen, J., Béland, M., Thomas, S., Achim, A., 2017. Removing bias from LiDAR-based estimates of canopy height: accounting for the effects of pulse density and footprint size. Remote Sens. Environ. 198, 1–16. https://doi.org/10.1016/j.rse.2017.05.032

Tabacchi, G., Di Cosmo, L., Gasparini, P., Morelli, S., 2011. Stima del volume e della fitomassa delle principali specie forestali italiane. Equazioni di previsione, tavole del volume e tavole della fitomassa arborea epigea. Consiglio per la Ricerca e la sperimentazione in Agricoltura. Trento. 412 pp. (*In Italian*).

Vizzarri, M., Tognetti, R., Marchetti, M., 2015. Forest Ecosystem Services: Issues and Challenges for Biodiversity, Conservation, and Management in Italy. Forests, 6, 1810-1838. https://doi.org/10.3390/f6061810

Zhao, K., Popescu, S., Meng, X., Pang, Y., Agca, M., 2011. Characterizing forest canopy structure with lidar composite metrics and machine learning. Remote Sens. Environ. 115, 1978–1996. https://doi.org/10.1016/j.rse.2011.04.001

Zhao, K., Suarez, J.C., Garcia, M., Hu, T., Wang, C., Londo, A., 2018. Utility of multitemporal lidar for forest and carbon monitoring: Tree growth, biomass dynamics, and carbon flux. Remote Sens. Environ. 204 883–897. https://doi.org/10.1016/j.rse.2017.09.007

Zolkos, S., Goetz, S., Dubayah, R., 2013. A meta-analysis of terrestrial aboveground biomass estimation using lidar remote sensing. Remote Sens. Environ. 128, 289–298. https://doi.org/10.1016/j.rse.2012.10.017

Planet Care from Space

Edited by Dessena M.A., Melis M.T and Rossi P. "***Planet Care from Space***" is the second volume of "***Trends in Earth observation***", a series published by the Italian Society of Remote Sensing (AIT).
This volume, organized in 7 thematic chapters, includes 45 contributions.

Edited by Dessena M.A, Melis M.T. and Rossi P.

Maria Antonietta Dessena works at the Regional Water Agency where (Enas) and she deals with the management and monitoring of water resources also by advanced technologies. She promote international cooperation projects for the use and enhancement of water resources at national and international level within the framework of APQ, ENI CBCMED, Horizon2020, etc. She was researcher at CORISA until 1993. This last two years she is responsible of PRIMEWATER projects within the Horizon2020 program on the theme of water quality assessment and short-term forecasts with the help of remote sensing and the MEDISS ENI CBCMED project. He has taught on remote sensing in numerous courses including FAO and UNESCO and from 2000 to 2003 as Professor in charge of the course of Remote Sensing at the University of Sassari. She is a member of AIT Association since 1986 and she is a member of the Board on AIT and on the ASITA Scientific Council. She is the author of more than 90 publications and co-author of book.

Maria Teresa Melis, graduated in Geology on 1985, PhD in Remote Sensing application to arid and semiarid geomorphological mapping. She is professor in Geomatics, and responsible for the TeleGIS Remote Sensing Laboratory, at the University of Cagliari, Italy. She was vice- President of the Italian Association of Remote Sensing and actually she is co-chair of the III Commission "Remote sensing" in ISPRS (International Society for Photogrammetry and Remote Sensing), Thematic Information Extraction. Member of the Scientific Council of ASITA (Federation of Italian Scientific Associations in Environmental and Land Information). Her research focuses on remote sensing applied to geological, land cover, and geomorphological analysis in remote areas (cold and hot arid lands), publishing +100 papers and contribution in books.

Patrizia Rossi is a permanent technologist since 2012 at the Department of Agriculture, Food, Environment and Forestry (DAGRI) at University of Florence
She graduated at the University of Florence where she obtained a Bachelor's Degree in Forest Science.
To date she deals with the technical management of the Geomatics Laboratory (geoLab) and she is involved in various projects on the use of Remote Sensing and GIS data. She is the Editorial Office Administrator of the European Journal of Remore Sensing, the internazional journal published by Taylor&Francis on behalf of AIT

ISSN 2612-7148
9 772612 714859
ISBN 978-88-944687-0-0
9 788894 468700