Application of Neural Networks for the retrieval of forest woody volume from SAR multifrequency data at L and C bands

Emanuele Santi, Simonetta Paloscia, Simone Pettinato, Gherardo Chirici, Matteo Mura & Fabio Maselli

Application of Neural Networks for the retrieval of forest woody volume from SAR multifrequency data at L and C bands

Emanuele Santi[1*], Simonetta Paloscia[1], Simone Pettinato[1], Gherardo Chirici[2], Matteo Mura[3] and Fabio Maselli[4]

[1]Institute of Applied Physics, National Research Council (IFAC - CNR), via Madonna del Piano 10, 50019 Florence, Italy
[2]Department of Agricultural, Food and Forestry Systems - Università di Firenze, Via San Bonaventura 13, 50145 Florence, Italy
[3]Dipartimento di Bioscienze e Territorio - Università del Molise, Contrada Fonte Lappone snc, 86090 Pesche (Isernia), Italy
[4]IBIMET- National Research Council of Italy (IBIMET-CNR), via Madonna del Piano 10, 50019 Florence, Italy
*Corresponding author, e-mail address: e.santi@ifac.cnr.it

Abstract

This work aims at investigating the potential of L (ALOS/PALSAR) and C (ENVISAT/ASAR) band SAR images in forest biomass monitoring and setting up a retrieval algorithm, based on Artificial Neural Networks (ANN), for estimating the Woody Volume (WV, in m^3/ha) from combined satellite acquisitions.

The investigation was carried out on two test areas in central Italy, where ground WV measurements were available.

An innovative retrieval algorithm based on ANN was developed for estimating WV from L and C bands SAR data. The novelty consists of an accurate training of the ANN with several thousands of data, which allowed the implementation of a very robust algorithm. The RMSE values found on San Rossore area were $\cong 40$ m^3/ha (L band data only), and 25-30 m^3/ha (L with C band). On Molise, by using combined data at L and C bands, RMSE<30m^3/ha was obtained.

Keywords: ANN, backscattering, Woody Volume, LiDAR, ALOS/PALSAR, ENVISAT/ASAR.

Introduction

The importance of forest monitoring is universally recognized due to the role played by forests and other semi-natural ecosystems in regulating the carbon cycle. Spatial explicit information at different scales on forest status is therefore needed in several technical and scientific applications; in particular, for monitoring a wide range of ecosystem services and for supporting the development of carbon and bioenergy policies, the detection of land-use

change and the assessment of carbon stocks [Corona et al., 2002].

The established practice of forest ecosystem inventory and monitoring is recognized as a main support for terrestrial natural renewable resource survey programs. Inventory and monitoring programs focused on an overall assessment of ecosystem attributes evolving into global environmental survey programs have been devised, but implementation is still quite limited. Their development and the implementation of approaches based on a sound "per habitat" landscape ecological perspective will bring unique benefits, thus leading to an effective integration among sector surveys aimed at global environmental inventory/ monitoring [Barbati et al., 2014].

Since local measurements are significantly affected by spatial heterogeneity, remote sensing techniques are an important tool for the classification of forests and the monitoring of their degradation due to cuttings, fires, and diseases. Optical sensors operating from satellite are widely adopted for this purpose, and the complexity of parameters that may be extracted from these observations can be increased through multi-temporal and multispectral image classification techniques, allowing the monitoring and classification of forests and their temporal evolution, and providing useful tools for the forest management [McRoberts et al., 2010]. However, optical bands can only operate in daylight and cloud-free conditions, which limit the monitoring of equatorial, boreal and mountainous areas. Moreover, in these spectral bands only the investigation of the upper layer of the canopies is allowed. Microwave frequencies can instead operate under cloud coverage, during night time and can penetrate through vegetation where radiation is scattered by stems, branches, twigs, leaves or needles. In particular, the lower portion of microwave spectrum was demonstrated to be suitable for observing the forests and investigating the temporal evolution of forest biomass. Extension of forests, their thermal state (frozen/thawed), biomass density, tree height and woody volume can be derived from the analysis of the backscattering data produced by synthetic aperture radar (SAR) systems [e.g. Eriksson et al., 2005; Santoro et al., 2008; Ackermann et al., 2012], especially after the launch of new sensors characterized by high spatial resolution and very frequent revisit time. The most suitable frequency for estimating forest biomass (generally expressed as the Woody Volume, WV, in m^3/ha) is P band due to the longer wavelength and consequent higher penetration in dense canopies. For this purpose, ESA approved the BIOMASS mission that is aimed at global mapping of the forest biomass with high accuracy [Le Toan et al., 2011]. The satellite will be launched in the near future, carrying onboard a SAR sensor operating at P- band. Higher frequencies (e.g. L and C bands) are still sensitive to forest parameters; however, Lband exhibits some saturation for high WV values (> 400 - 500 m^3/ha) and C band, with its scarce penetration inside the vegetation cover, is only sensitive to the first layers of the crowns. The latter frequency is more suitable for classification purposes and investigation of forest features related to degradation [Dobson et al., 1992; Le Toan et al., 1992; Beaudoin et al., 1994; Israelsson et al., 1994; Rauste et al., 1994; Paloscia et al., 1999].

The use of multi-frequency and multi-polarization approaches can therefore provide accurate results, being able to characterize the different layers of the trees. In this context, the Artificial Neural Networks (ANN) represent definitely an efficient tool for merging and assimilating data from different sources into a unique retrieval approach, setting up a multi-frequency and multi-polarization technique, which is able to increase the retrieval accuracy with respect to more conventional methods. ANN can be trained to represent arbitrary input-

output relationships [Hornik, 1989; Linden and Kinderman, 1989]. During the training phase, training patterns are sequentially presented to the network and the interconnecting weights of each neuron are adjusted according to a learning algorithm. The trained ANN can be considered as a type of non-linear least mean square interpolation formula for the discrete set of data points in the training set. This technique has been successfully applied to many inverse problems in the remote sensing field. The comparison between some retrieval algorithms for the estimate of soil moisture content, carried out in Paloscia et al. [2008], demonstrated that ANN, with respect to other widely adopted statistical approaches based on Bayes theorem and Nelder-Mead minimization, offer the best compromise between retrieval accuracy and computational cost. However, ANN in some cases have been used essentially as a black box, without further effort for understanding the underlying processes and the physics behind them. The strategy for minimizing these problems is mainly based on the use of extensive datasets, obtained from experimental data archives, for the training phase of ANN, which is the more thorny issue. A special attention should be paid in the optimal configuration setting and in the number and choice of input parameters. A few examples of ANN application to SAR data for the retrieval of WV can be found in literature [e.g. Del Frate and Solimini, 2004; Amini and Sumantyo, 2011]. In Amini and Sumantyo [2011] SAR and optical images are used as input for a multilayer perceptron neural network (MLPNN) that relates them to the forest measurements on the ground, while in Del Frate and Solimini [2004] the application of ANN for retrieving forest biomass from multi-polarization backscattering at L and P band is evaluated using experimental data and model simulations.

In this paper, the sensitivity of backscattering coefficient ($\sigma°$) at L and C bands, measured by the SAR systems of ALOS/PALSAR and ENVISAT/ASAR sensors, to the forest biomass (expressed as Woody Volume, WV, in m^3/ha), is first of all investigated, by comparing the available SAR acquisitions at L and C bands with WV. The WV was derived from both conventional measurements and LiDAR acquisitions in two test areas covered by forests in Italy.

Basing on the results of this sensitivity analysis, a retrieval algorithm based on ANN techniques for estimating WV from the multi-frequency and multi-polarization acquisitions of these SAR sensors was implemented and validated separately in both areas. The capabilities of ANN in merging inputs from different sensors allowed accounting for the sensitivities to different forest layers exhibited by the two bands, and the severe training, which represents the most delicate step of the ANN algorithm implementation, mitigated the risks of this process. The innovation of this approach consists of the use of ANN specifically trained with several thousands of data and by paying special attention to the setting of the input parameters. Moreover, a part of the available data set was retained for an independent validation after completing the conventional training, test and validation actions, as it will be better specified in the following sections. The obtained results have been presented in terms of R and RMSE.

Test areas and experimental data

The two test areas considered for this work are located in the central part of Italy, and are mostly covered by forests of various species. WV measurements from LiDAR acquisitions and conventional methods were available for both areas:

a) San Rossore (43.72° N - 10.30° E) is a flat area covered by forests along the coast of Tuscany (4800 ha). The land cover is dominated by the presence of Mediterranean pines (*Pinus pinaster* Ait., *P. pinea* L.), *Quercus ilex* L., and several other species known as Mediterranean 'macchia'. As ground truth, a Woody Volume (WV, in m³/ha) map derived from the LiDAR acquisition of June 2009 has been used [Bottai et al., 2013] along with conventional WV measurements on 72 pine forest plots not covered by the LiDAR acquisition.

b) Molise (41.50° N - 14.15° E), in the South-West part of Molise Region (31950 ha). Forests cover about the 64% of the area and are represented by several broad-leaf species: Turkey oak (*Quercus cerris*) (29.81%), Downy oak (*Quercus pubescens*) (28.69%), Hop Hornbeam (*Ostrya carpinifolia*) (17.70%), Beech (*Fagus sylvatica*) (9.04%), Holm oak (*Quercus Ilex*) (6.88%). Also in this case a WV map from LiDAR acquired in June 2009 was available along with 260 conventional measurements on forest plots outside the LiDAR acquisition.

The location of both areas is shown in the map of Figure 1.

Figure 1 - Map of the two test areas considered in this work.

Table 1 - List of available SAR images for each test site.

Test area	SAR sensor	Polarizations	Date
San Rossore	ENVISAT/ASAR	VV pol.	26/05/2009
	ENVISAT/ASAR	VV pol.	27/06/2009
	ENVISAT/ASAR	VV pol.	16/07/2009
	ALOS/PALSAR	Full-polarimetric	07/06/2009
	ALOS/PALSAR	HH and HV	16/07/2009
Molise	ENVISAT/ASAR	VV pol.	18/06/2009
	ALOS/PALSAR	HH and HV	19/06/2009

On the test area of San Rossore, SAR images listed in Table 1 were available, together with:

- WV map from an airborne LiDAR acquisition of 02/06/2009, validated on the Pinus pinea forest (about 708 ha) and considered as a reference ground truth for exploiting the potential of SAR data in WV monitoring.
- Conventional WV measurements on 72 plots of forest outside the area covered by LiDAR acquisitions. The area of these plots ranged between 1 and 170 ha, the plots were covered by 3 types of forest: Mediterranean pine, holm and deciduous trees. These data were considered for an independent validation of the retrieval algorithm based on ANN.

A similar dataset was available on the Molise test area (see Tab. 1), integrated by the following data:

- WV map from LiDAR of 36.380 ha considered as ground truth for setting up the retrieval algorithm.
- Conventional WV measurements on more than 260 forest plots outside the area covered by LiDAR acquisitions. Each sample refers to an area of about 500 m^2. This dataset was considered for the independent validation.

The SAR images were geocoded by using a digital elevation model derived (DEM) from the Shuttle Radar Topography Mission (SRTM). The SAR images in a slant-range format have a pixel size of about 9×3 m^2 for PALSAR FBD, 5×3 m^2 for PALSAR FBS and 8×4 m^2 for ASAR IMS.

Each image was processed by applying a multilook process, in order to average the intensity in range and azimuth direction, by using the appropriated window size according the considered SAR sensor. The radiometric calibration was performed considering the local incidence angle based on the orbital parameters and the DEM, that combined with satellite orbital parameters allowed also the identification of layover and shadow effects. Layover and shadowing were almost negligible in the flat area of San Rossore, but affected some parts of the mountainous test site of Molise. The geocoded images have a pixel size of 10×10 m^2, and were co-registered in order to be comparable 'pixel by pixel' to each other and with other information, such as the local incidence angle (LIA), layover and shadow, and LiDAR map: the common area between SAR and LiDAR acquisitions resulted in 710x520 pixels at a resolution of 10x10 m^2. The subset on the pine forest only is composed by more than 70000 pixels.

Afterwards, the correlation between SAR signal and WV estimated by LiDAR was

investigated. Only negligible variations in forest WV were expected in the temporal interval covered by these images; however, slightly higher correlations were found when comparing the LiDAR acquisitions with ASAR and PALSAR images collected in the closest dates, i.e. 26/05/2009 for ASAR and 07/06/2009 for PALSAR, respectively. The obtained logarithmic regression equations between $\sigma°$, from both PALSAR (L band) and ASAR (C band) data, and WV were the following:

San Rossore:
$\sigma°VV=0.67\ln(WV)-14.51$ (ASAR)
$\sigma°HH=1.60\ln(WV)-19.16$ (PALSAR)
$\sigma°HV=1.95\ln(WV)-26.28$ (PALSAR)

Molise:
$\sigma°VV=0.25\ln(WV)-8.3$ (ASAR)
$\sigma°HH=0.91\ln(WV)-14.40$ (PALSAR)
$\sigma°HV=1.35\ln(WV)-21.93$ (PALSAR)

The value of the correlation coefficients (R) varies depending on the window size of the despeckling filter applied to the SAR images. The correlation increased passing from 3x3 window (average correlation coefficient, R= 0.33) up to 20x20 window (average R= 0.52): the latter case corresponds to a ground resolution of about 200 x 200m². Larger windows did not produce any further increase in the correlation coefficient. The correlation coefficients between the $\sigma°$, at C and L band in different polarizations, and the WV estimated by LiDAR for the Pine forest of San Rossore are listed in Table 2.

Table 2 - Minimum and maximum value of the correlation coefficient (R) obtained from the comparison between SAR and LiDAR data on San Rossore area, depending on the despeckling filter size.

R	ASAR VV	PALSAR VH	PALSAR HV	PALSAR HH	PALSAR VV
3x3	0.16	0.40	0.38	0.32	0.37
20x20	0.26	0.62	0.61	0.52	0.60

As expected, ALOS/PALSAR $\sigma°$ at L band is better correlated than the ENVISAT/ASAR C band $\sigma°$ to the WV estimated by LiDAR. Especially the L band acquisitions collected at cross-pol (VH or HV) are the most correlated to the forest WV (R>0.6).
The sensitivity of $\sigma°$ to the WV is also represented in the occurrence plot of Figure 2, in which the PALSAR $\sigma°$ in HV polarization is plotted as a function of the WV obtained from LiDAR measurements. A clear correlation between $\sigma°$ and WV and a saturation of the signal for WV values higher than 400-500 m³/ha can be observed. The high values of both WV and $\sigma°$ have the highest occurrence.
The same analysis was carried out for the Molise area. In this case, nevertheless, the presence of different species of trees and the orography effects decreased the correlation between SAR $\sigma°$, LiDAR and ground truth data. The sensitivity of microwaves to the water content of the observed targets makes the measured signal less dependent on the forest type, since the driving factor for the scattering is directly related to the fresh biomass; however,

the different characteristics of trees affect in some way the correlation between SAR data and LiDAR estimates.
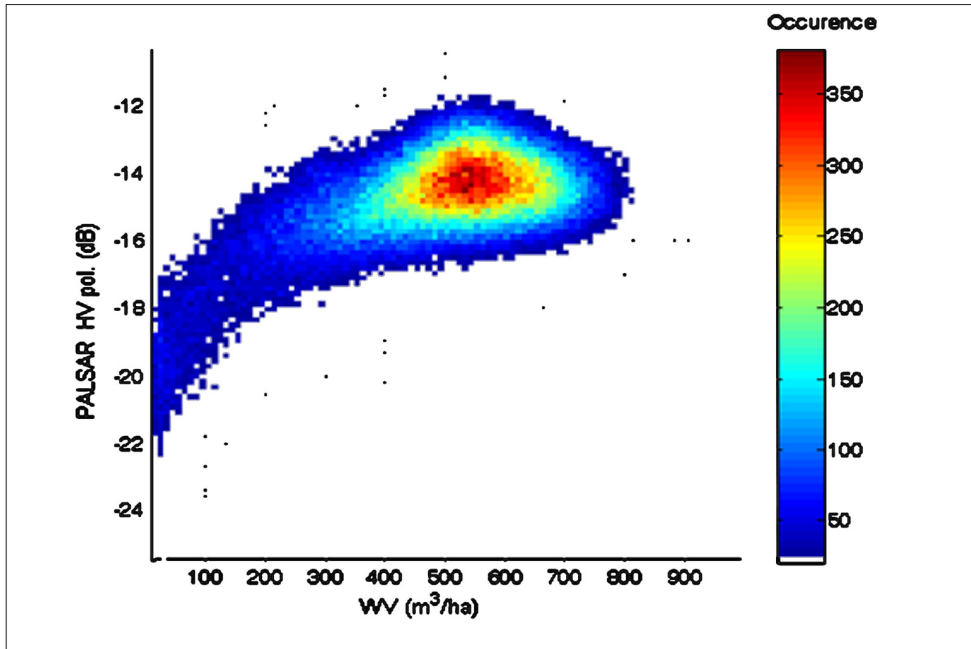
Figure 2 - Occurrence plot of PALSAR L band σ° in HV pol. as a function of biomass (Woody Volume, in m³/ha) for the Pine forest of San Rossore.

Moreover, the large variations in the Local Incidence Angles (LIA) due to the mountainous nature of the area, has a significant influence on the measured signal, lowering the correlation between σ° and WV. After filtering out the layover and foreshortening areas, only data collected at the nominal incidence +/- 2σ were therefore retained, which correspond to the range 18°-58° for PALSAR and 6°-44° for ASAR, in order to discard data collected at extreme incidences, in which the observation angle, although compensated, affects noticeably the measured signal. After this filtering process, the correlation between backscattering and WV reached values comparable to the San Rossore test area. The correlation coefficients are listed in Table 3, while the occurrence plot of the filtered data is represented in Figure 3. In this case, the highest occurrence is associated to the low values of both WV and σ°.

Table 3 - Minimum and maximum value of the correlation coefficient (R) derived from the comparison between SAR σ° and LiDAR data on Molise area, depending on the despeckling filter size.

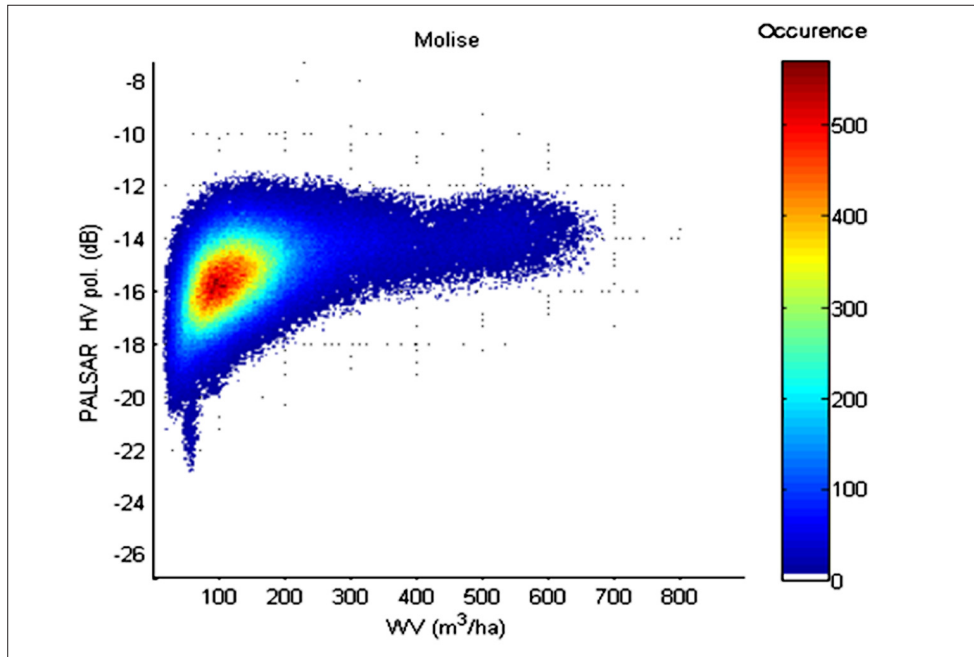| R	ASAR VV	PALSAR HV	PALSAR HH
3x3	0.05	0.45	0.29
20x20	0.07	0.61	0.46

Figure 3 - Occurrence plot of PALSAR L band σ° in HV pol. as a function of WV for the mixed forest of Molise.

In spite of the large differences in acquisition geometry and tree species encountered in the two areas, we noted that the backscattering shows a marked sensitivity to WV, especially at L band, although the different characteristics of each site influenced the relationship between these two parameters.

Development of the inversion algorithm

The demonstrated sensitivity of SAR σ° to forest biomass, although site dependent, suggested implementing an inversion algorithm for estimating WV from SAR acquisitions at L and C bands. In order to better exploit the contribution of each available frequency and polarization to the retrieval, the algorithm was based on ANN methods that allow an easy but effective assimilation of data from different sources. The main constraint for obtaining a good accuracy with ANN approaches, as it has been demonstrated in [Paloscia et al., 2008], is represented by the "robustness" of the training, which has to be representative of a variety of surface conditions as wide as possible, in order to make the algorithm able to associate the proper output to each input, by filtering out the signal variability due to the local surface features. Past papers published by the authors [e.g. Paloscia et al., 2008, 2013] devoted to the estimate of soil moisture content, pointed out the potential of the ANN technique in easily and effectively ingesting information extracted from different sources for improving the retrieval process. The importance of a robust and extensive reference dataset for the training was generally confirmed, in order to obtain a retrieval algorithm able to work at different scales with a satisfactory accuracy.

The ANN considered in this study are Multi-Layer Perceptrons (MLP). The algorithm

chosen for the training phase is the back-propagation (BP) learning rule, an iterative gradient descent algorithm designed to minimize the mean square error between the desired target vectors and the actual output vectors [Hornik, 1989; Linden and Kinderman, 1989]. It should be noted that the gradient-descent method sometimes suffers from slow convergence, due to the presence of one or more local minima, which may also affect the final result of the training. In order to overcome this problem, the training was repeated several times, with a resetting of the initial conditions and a verification that each training process led to the same convergence results in terms of R^2 and RMSE, by increasing it until negligible improvements were obtained. This was done in order to define the minimal ANN architecture that is able to provide an adequate fit for the training data, thus preventing overfitting problems. Overfitting is related to the oversizing of the ANN, and may cause considerable errors when testing ANN with input data that is not included in the training set.

To define the optimal ANN architecture, after the training phase, the ANN was tested using data not included in the training set, and the training and testing results were then compared. The ANN configuration was then increased, until the ANN architecture was found to have a negligible improvement in the training and a worsening in the test results. Inputs of each ANN were the SAR acquisitions at the available frequencies and polarizations, the incidence angles and the ancillary data, and the output is the forest WV.

ANN algorithm for San Rossore

In order to evaluate the contribution of each available frequency and polarization, several configurations of inputs have been defined, and for each configuration a dedicated ANN was trained. In particular, the retrieval performances were evaluated considering as inputs the ALOS/PALSAR HH/HV with or without ENVISAT/ASAR VV, the PALSAR VV/VH with or without ASAR VV, the PALSAR full polarimetric and the PALSAR full-polarimetric plus ASAR VV. Training and test were carried out by dividing the available dataset, i.e. the 70000 co-located SAR and LiDAR pixels, in two subsets of 35000 samples each. The first subset was again divided randomly in 60% - 20% -20% for training, test and validation phase, respectively. An architecture of three hidden layers of 11-11-10 neurons, derived from the optimization process, was considered for all the 6 different cases. Each trained ANN was then applied to the second subset of 35000 samples for an independent validation. The use of PALSAR data only, either VV/VH or HH/HV, gave the poorest results, with R >0.85 and RMSE <40 m³/ha, while the use of all the 4 polarizations did not improve appreciably this result, probably because the two cross polarized ALOS signals are well correlated each other (R=0.99), and therefore the independent information provided by this channel is negligible.

The addition of ASAR data in the ANN inputs allowed instead a significant accuracy improvement, although C band data are generally less correlated with the WV. The best results were indeed obtained considering the PALSAR HH/HV plus ASAR VV combination or PALSAR full-pol. plus ASAR VV, with a correlation of 0.92 and 0.94 and a RMSE of 30 and 25 m³/ha, respectively. Plots of Figure 4 represent the results of this independent test for the PALSAR HH/HV, PALSAR 4 pol, PALSAR 2 pol. + ASAR VV and PALSAR 4 pol. + ASAR VV, respectively.
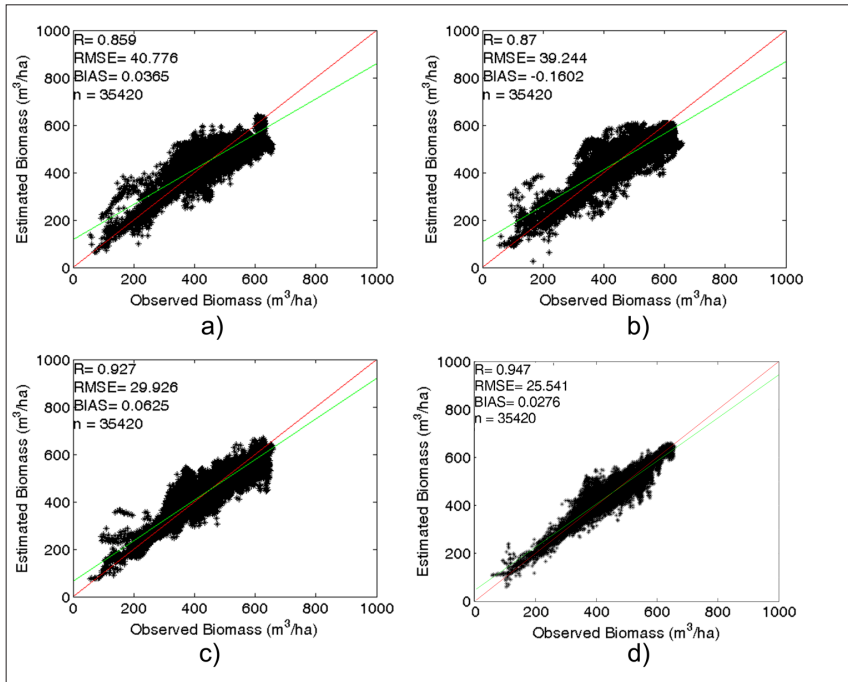
Figure 4 - WV estimated by the ANN algorithm as a function of the corresponding ground truth considering as input on San Rossore area: a) PALSAR HH/HV, b) PALSAR 4 pol., c) PALSAR 2 pol. +ASAR and d) PALSAR 4 pol. +ASAR.
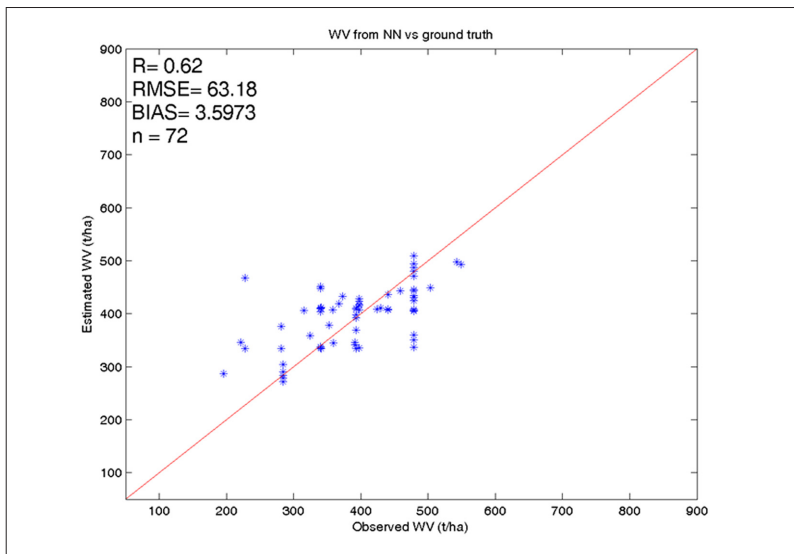

Figure 5 - WV estimated by the ANN algorithm as a function of the corresponding ground truth on San Rossore area obtained by considering the PALSAR 2pol. + ENVISAT inputs for the 72 plots of the independent validation.

Finally, an independent validation was carried out on the 72 forest plots falling outside the LiDAR map, for which conventional measurements of WV were available. Two factors that significantly affect the retrieval accuracy are the unknown correlation between conventional and LiDAR based WV measurements, and the inclusion of other forest species in the dataset. Nonetheless, the result represented in Figure 5, that corresponds to a correlation coefficient R=0.62, RMSE= 63.18 m³/ha and p <0.01, can be still considered satisfactory.

ANN algorithm for Molise

Following the approach previously implemented for the San Rossore area, a second algorithm, still based on ANN, was implemented and tested on the available dataset. In order to verify the best combination of frequencies and polarizations for the retrieval, this analysis was carried out independently of the results obtained for San Rossore, and this second algorithm was developed only considering data from Molise. The dataset resulting from filtering process was significantly larger, being composed of about 260.000 samples. As for the San Rossore test site, training and test were carried out by splitting the dataset in two subsets of about 130.000 samples each, with a random sampling. The first subset was again divided randomly in 60% - 20% -20% for training, test and validation phase, respectively. The random sampling of the dataset was reiterated 5-6 times and the training was repeated, in order to avoid any dependence of the obtained results on the sampling process.
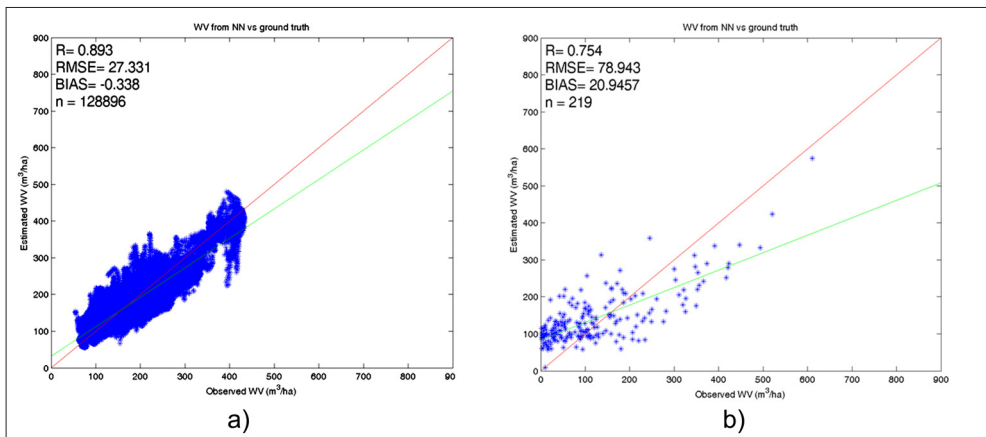

Figure 6 - WV estimated by the ANN algorithm vs a) the corresponding LiDAR estimated values and b) vs. the plots with conventional WV measurements outside the LiDAR map for Molise area.

The result of the test is represented in Figure 6 a, while Figure 6 b shows the result of the independent validation on the forest plots outside the LiDAR map. For the validation on the forest plots with conventional WV measurements, represented in Figure 6 b, the same considerations of the corresponding result for San Rossore can be done: the relationship between these measurements and the WV from LiDAR cannot be verified, but the result can be considered satisfactory and it represents a really independent validation of the algorithm. Moreover, several WV values in this dataset are lower than the minimum WV obtained from LiDAR in the training set. These low biomass values have not been properly treated

by the algorithm that strongly overestimates them, as it is evident from the plot of Figure 6b. The decreased number of plots considered in Figure 6b depends on the filtering of SAR data for layover/shadowing and extreme angles.

Results

After completing the three steps of training, testing and validation, the ANN algorithms have been applied to the whole areas for generating WV maps to be compared with the corresponding map from LiDAR. The maps of Figure 7a (WV from SAR) and 7b (WV from LiDAR) represent such comparison for the San Rossore pine forest. These maps confirmed the ability of the algorithm in estimating the forest WV from SAR data, with a slight underestimate of the highest WV values, depending on the signal saturation for the high WV values.
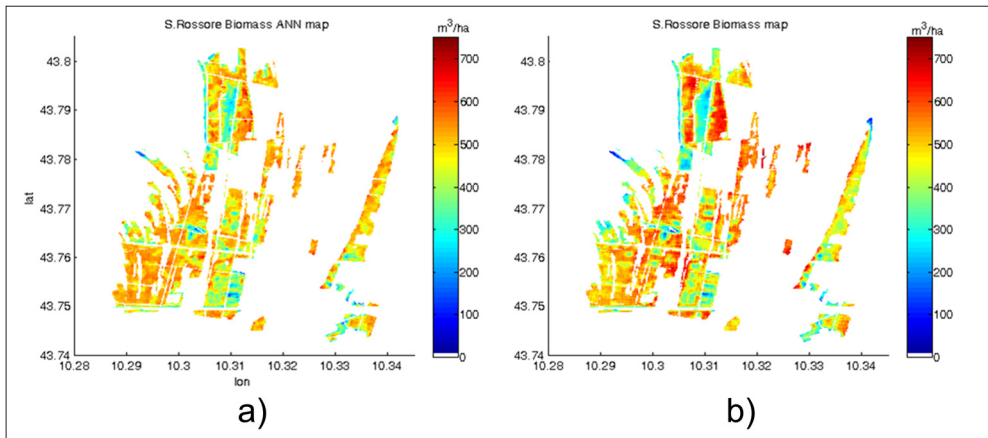

Figure 7 - Comparison of WV maps for the pine forest of San Rossore, generated from SAR (a) and from LiDAR measurements (b)
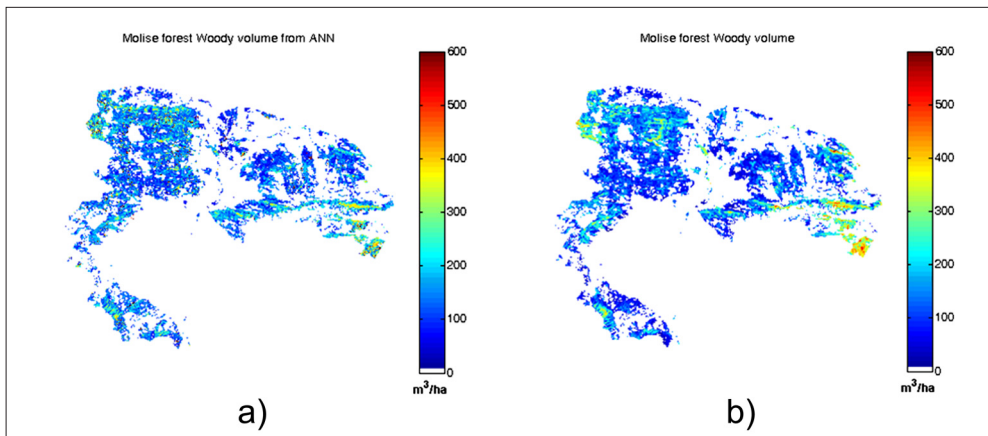

Figure 8 - Maps of WV for the Molise forests, generated from SAR with ANN algorithm (a) and LiDAR (b)

Figure 8 shows instead the WV maps of Molise derived from ANN algorithm applied to SAR data (a) and from LiDAR (b). These maps reflect the accuracy of the ANN test (Fig. 6a): the WV values from LiDAR are fairly well reproduced, with a slight underestimate of the highest values, as in San Rossore maps.

Conclusions and future work

As demonstrated in past research, L and C band are not the most suitable frequencies for the monitoring of forest biomass from microwave sensors, due to the signal saturation for WV values higher than 400-500 m^3/ha at L band, and to the scarce penetration power inside the forest cover at C band. Waiting for BIOMASS data at P band, the results of the proposed technique can be considered encouraging, exploiting the potential of the L and C bands for WV monitoring from existing SAR sensors. Moreover, it should be mentioned that the WV range between 0 and 400-500 m^3/ha is of particular importance for the prediction of net forest carbon uptake, due to the high capacity of young, not fully stocked ecosystems to accumulate new woody tissue [Maselli et al., 2009].

An innovative algorithm based on ANN methods was implemented, by exploiting the power of ANN in merging data from different sources and minimizing the risks of this type of statistical procedure with a severe training. For this step of the procedure, we used experimental data sets of several thousands of data and half of the available data set for a further validation. When ANN are correctly set, trained, and tested the risk of errors caused by a blind use is really reduced.

The different characteristics of the two areas in terms of vegetation species, orography, and landscape features brought to the implementation of two different ANN. The results obtained so far are really encouraging: by using L band only we have obtained R=0.86 and RMSE=40 m^3/ha on San Rossore area; whereas the combined use for C and L bands led to R=0.95 and RMSE=25-30m^3/ha. On Molise area, we have obtained similar results: R=0.89 and RMSE=27m^3/ha.

An independent validation on forest samples outside the LiDAR map where conventional ground measurements were carried out was performed on both areas. On San Rossore we obtained R=0.6 and RMSE=60m^3/ha and on Molise R=0.75 and RMSE=78m^3/ha. This final validation led to somewhat worse results due to the correlation between conventional and LiDAR based WV measurements and the inclusion of other forest species in the dataset.

Finally, the WV maps obtained from the algorithms were compared to the ones obtained from LiDAR, showing a very good similarity on both areas.

Looking at an operational application of this method, the implementation of a general retrieval algorithm able to work on all forest plots independently of the observation geometry and of the forest features will represent the next step of this research. This implies gathering more datasets from other test sites, in order to make the training phase as representative as possible of the different observation geometries, tree species, and other surface features. Data simulated by electromagnetic models should also be considered in order to fill in the gaps in the experimental data and extend the representativeness of the training. Setting up a more "representative" training process will allow the implementation of a robust algorithm able to work with satisfactory accuracy on different sites.

Acknowledgments

References

Ackermann N., Thiel C., Borgeaud M., Schmullius C. (2012) - *Cosmo-SkyMed backscatter intensity and interferometric coherence signatures over Germany's low mountain range forested areas*. IEEE International Geoscience and Remote Sensing Symposium, Munich, 22-27 July 2012, pp. 5514-5517. doi: http://dx.doi.org/10.1109/IGARSS.2012.6352357.

Amini J., Sumantyo J.T.S. (2011) - *SAR and Optical Images for Forest Biomass Estimation. Biomass - Detection, Production and Usage*. InTech, Matovic D. (Ed.) doi: http://dx.doi.org/10.5772/18930.

Barbati A., Marchetti M., Chirici G., Corona P. (2014) - *European Forest Types and Forest Europe SFM indicators: Tools for monitoring progress on forest biodiversity conservation*. Forest Ecology and Management, 321: 145-157. doi: http://dx.doi.org/10.1016/j.foreco.2013.07.004.

Beaudoin A., Le Toan T., Goze S., Nezry E., Lopes A., Mougin E., Hsu C.C., Han H.C., Kong J.A., Shin R.T. (1994) - *Retrieval of forest biomass from SAR data*. International Journal of Remote Sensing, 15: 2777-2796. doi: http://dx.doi.org/10.1080/01431169408954284.

Bottai L., Arcidiaco L., Chiesi M., Maselli F. (2013) - *Application of a single-tree identification algorithm to LiDAR data for the simulation of stem volume current annual increment.* Journal of Applied Remote Sensing, 7 (1): 073699. http://dx.doi.org/10.1117/1.JRS.7.073699.

Corona P., Chirici G., Marchetti M. (2002) - *Forest ecosystem inventory and monitoring as a framework for terrestrial natural renewable resource survey programmes*. Plant Biosystems, 136: 69-82. doi: http://dx.doi.org/10.1080/11263500212331358531.

Del Frate F., Solimini D. (2004) - *On Neural Network Algorithms for Retrieving Forest Biomass From SAR Data*. IEEE Transaction on Geoscience and Remote Sensing, 42 (1): 24-34. doi: http://dx.doi.org/10.1109/TGRS.2003.817220.

Dobson M.C., Ulaby F.T., Le Toan T., Beaudoin A., Kasischke E.S., Christensen Jr N.L. (1992) - *Dependence of radar backscatter on coniferous forest biomass*. IEEE Transaction on Geoscience and Remote Sensing, 30: 412-415. doi: http://dx.doi.org/10.1109/36.134090.

Eriksson L.E.B., Askne J., Santoro M., Schmullius C., Wiesmann A. (2005) - *Stem volume retrieval with spaceborne L band repeat-pass coherence: multi-temporal combination for boreal forest.* IEEE International Geoscience and Remote Sensing Symposium, 5: 3591-3594. doi: http://dx.doi.org/10.1109/IGARSS.2005.1526624.

Hornik K. (1989) - *Multilayer feed forward network are universal approximators*. Neural Networks, 2 (5): 359-366. doi: http://dx.doi.org/10.1016/0893-6080(89)90020-8.

Israelsson H., Askne J., Sylvander R. (1994) - *Potential of SAR for forest bole volume estimation*. International Journal of Remote Sensing, 15: 2809-2826. doi: http://dx.doi.org/10.1080/01431169408954286.

Le Toan T., Beaudoin A., Riom J., Guyon D. (1992) - *Relating forest biomass to SAR data*. IEEE Transaction on Geoscience and Remote Sensing, 30: 403-411. doi: http://dx.doi.org/10.1109/36.134089.

Le Toan T., Quegan S., Davidson M., Balzter H., Paillou P, Papathanassiou K., Plummer S., Saatchi S., Shugart H., Ulander L. (2011) - *The BIOMASS Mission: Mapping global forest biomass to better understand the terrestrial carbon cycle*. Remote Sensing of Environment, 115 (2011): 2850-2860. doi: http://dx.doi.org/10.1016/j.rse.2011.03.020.

Linden A., Kindermann J. (1989) - *Inversion of multi-layer nets* In Proceedings of International Joint Conference on Neural Networks, II: pp. 425-430. doi: http://dx.doi.org/10.1109/IJCNN.1989.118277.

McRoberts R E., Cohen W.B., Naesset E., Stehman S.V., Tomppo E.O. (2010) - *Using remotely sensed data to construct and assess forest attribute maps and related spatial products*. Scandinavian Journal of Forest Research, 25: 340-367. doi: http://dx.doi.org/10.1080/02827581.2010.497496.

Maselli F., Chiesi M., Moriondo M., Fibbi L., Bindi M., Running S.W. (2009) - *Integration of ground and satellite data to simulate the forest carbon budget of a Mediterranean region*. Ecological Modelling, 220: 330-342. doi: http://dx.doi.org/10.1016/j.ecolmodel.2008.10.002.

Paloscia S., Macelloni G., Pampaloni P., Sigismondi S. (1999) - *The Potential of L- and C- Band SAR in Estimating Vegetation Biomass: The ERS-1 and JERS-1 Experiments*. IEEE Transactions on Geoscience and Remote Sensing, 37 (4): 2107-2110. doi: http://dx.doi.org/10.1109/36.774723.

Paloscia S., Pampaloni P., Pettinato S., Santi E. (2008) - *A Comparison of Algorithms for Retrieving Soil Moisture from ENVISAT/ASAR Images*. IEEE Transaction on Geoscience and Remote Sensing, 46: 3274-3284. doi: http://dx.doi.org/10.1109/TGRS.2008.920370.

Rauste Y., Häme T., Pulliainen J., Heiska K., Hallikainen M. (1994) - *Radar-based forest biomass estimation*. International Journal of Remote Sensing, 15: 2797-2808. doi: http://dx.doi.org/10.1080/01431169408954285.

Santoro M., Askne J., Beer C., Cartus O., Schmullius C., Wegmuller U., Wiesmann A., (2008) - *Automatic Model Inversion of Multi-Temporal C band Coherence and Backscatter Measurements for Forest Stem Volume Retrieval*. IEEE International Geoscience and Remote Sensing Symposium, Boston, 7-11 July 2008, V: 124-127. doi: http://dx.doi.org/10.1109/IGARSS.2008.4780043.