On Neural Network Algorithms for Retrieving Forest Biomass From SAR Data

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***Abstract*—We discuss the application of neural network algorithms (NNAs) for retrieving forest biomass from multifrequency (L- and P-band) multipolarization (hh, vv, and vv) backscattering. After discussing the training and pruning procedures, we examine the performances of neural algorithms in inverting combinations of radar backscattering coefficients at different frequencies and polarization states. The analysis includes an evaluation of the expected sensitivity of the algorithm to measurement *noise* stemming both from speckle and from fluctuations of vegetation and soil parameters. The NNA accomplishments are compared with those of linear regressions for the same channel combinations. The application of NNAs to invert actual multifrequency multipolarization measurements reported in literature is then considered. The NNA retrieval accuracy is now compared with those yielded by linear and nonlinear regressions and by a model-based technique. A direct analysis of the information content of the radar measurements is finally carried out through an extended pruning procedure of the net.**

***Index Terms*—Forest biomass, neural networks, synthetic aperture radar (SAR).**

I. Introduction

In recent years, research in remote sensing has led to the development of methods for retrieving forest parameters from backscattering data collected by synthetic aperture radar (SAR). This effort stems from the importance of forestry monitoring in facing several environmental problems, in particular for rapid damage assessment (in southern Europe forest fires destroy vast areas each year) and disease detection (in relation to a severe acidification stress in some regions). Moreover, on a global scale, as they comprise about 90% of the terrestrial biomass, forests play a crucial role in hydrologic, climatic and biochemical cycles [1]–[3]. Besides, forest stand parameters may be useful information for the timber industry, as well as for environment management agencies.

A major problem in forest biomass retrieval from SAR data is the contamination of radar measurements by a number of other environmental variables. To mitigate the effect, multifrequency and multipolarization datasets have been mainly considered, collected by airborne (AirSAR) [4]–[8] and shuttleborne (SIR-C/X-SAR) [9]–[12] SAR. Some attempts to exploit single-channel satellite intensity data have also been reported [13]–[15], with promising results attained when data taken at two frequencies (for the European Remote Sensing satellite and the Japanese Earth Resources Satellite) are combined [16], or when measurements are taken at lower frequencies (e.g., VHF) [17]. Multitemporal interferometric satellite measurements are now being also favorably considered for forest monitoring [18]–[21].

Retrieving forest stand volume or biomass from backscattering data has often been carried out by implementing linear and nonlinear multiple regressions [4], [8], [9], [22]–[24]. To overcome the ill-posedness of the problem, a methodology exploiting *a priori* classification of arboreous vegetation and extensive use of a biophysical model has been proposed and tested [11]. According to the high accuracy of the reported results, such a retrieval scheme is expected to allow progress in forest parameters estimation. However, its performance is dependent on the precision of antecedent classification, and moreover, its extension to a global context is somewhat hampered by the cited "regional nature of the allometric relationships."

An alternative approach, based on neural network algorithms (NNAs), which are becoming commonly available and readily usable, has been devised to retrieve environmental parameters from radar data [25]–[30]. Their use in remote sensing has been often found effective, since they can simultaneously handle nonlinear mapping of a multidimensional input space onto the output one and cope with complex statistical behavior. Indeed, it has been shown that a multilayer perceptron (MLP) [31] with a single hidden layer and nonlinear activation functions is capable of approximating any real-valued continuous function, provided a sufficient number of units within this hidden layer exists [32]. However, while a general MLP can form arbitrary mappings, in practice, finite network size demands that only an approximation to the optimal solution can ever be achieved. In addition, an NNA is apt to be, and in most cases has been, used essentially as a black box; hence, the underlying processes that give rise to the network behavior and performance are not discerned. An additional criticism stems from the long time usually required by the training phase.

Our work is focused onto clarifying some features and discussing the performances of NNAs for retrieving forest biomass density from multifrequency multipolarization SAR data. Particular attention is paid to the robustness of the algorithms with respect to perturbations of the nominal vegetation and soil conditions, as well as to one kind of *noise* intrinsic to SAR measurements. NNAs are tested in estimating biomass from actual measurements taken over diverse forest types (from boreal to tropical), with the main purpose of appreciating the performance of a neural net when put to use in a real and global context. We point out that this retrieval problem is considered to be difficult,

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especially if one takes into account the observed noticeable saturation of the single backscattering coefficients versus biomass, even at lower (P-band) radar frequencies, and the number of variables which affect the measurements. With respect to this, a set of neural net algorithms tuned to each relevant class of vegetation is expected to yield better results than a unique algorithm. However, it is still interesting to estimate the performance and assess the limits of a single retrieval scheme of a more general applicability.

This paper is organized with the following scheme.

- First, we study the use of NNAs trained on model simulations to invert simulated backscattering values.
- Then, we consider the use of NNAs trained on experimental data to invert real measured backscattering values.
- Finally, the use of NNAs trained on model simulations to invert experimental (conifer) data is discussed.

Our simulation analysis concerns the estimate of the biomass of conifer stands from L- and P-band co- and cross-polarized backscattering coefficients (σ^0). The retrieval tool is a feedforward two-hidden-layer perceptron with one, three or six input elements and a single output. The simulated σ^0 are computed by an electromagnetic model developed at Tor Vergata [33]. To simulate the natural variability of the soil and vegetation parameters, perturbations in soil moisture content (SMC) and understory biomass density (UBD) have been selected among the many possible choices. Random fluctuations of SMC and of UBD have been generated and superimposed to their nominal values to obtain perturbed σ^0 sets on which the NNAs have been tested. Similarly, the effect of speckle has been introduced by generating random fluctuations of backscattering about its nominal value. The sensitivity of the NNA to these kinds of perturbation in the surface or in the measurement conditions has been analyzed, keeping the commonly used statistical regressions as a benchmark. The feasibility of using NNAs, trained both with experimental and with model data, for retrieving real-world data taken on different forest types, including conifers, poplar, and mangrove, is then considered. A discussion on the information content of the individual radar channels and frequencies is finally conducted by comparing NNA retrieval accuracies for different sets of real measurements.

II. How NNAs Perform on Noisy Data

Backscattering from natural surfaces is heavily affected by a number of variables, so that the information content of σ^0 on a single parameter is often mixed up and difficult to retrieve. If vegetation biomass is sought for, both essentially temporal factors, like rain or drought, and spatial factors, like soil roughness or plant type, join to reduce the overall sensing accuracy. The problem is further compounded by speckle, which increases the fluctuations of measured σ^0, adding to system noise and calibration errors. Algorithms, which, besides exploiting different pieces of information, are robust, must then be invoked to try to overcome this burden.

Multiple-input NNAs at least match the exigency of profiting by several measurements. Their robustness with respect to perturbations in the nominal measurement conditions remains to be evaluated.

This aspect is examined in the simulation analysis reported in the following.

A. Training and Testing the NNA

The Stuttgart neural network simulator (SNNS) developed at the University of Stuttgart (Germany) [34] has provided the basic software for the algorithm implementation. As far as the topology is concerned, we referred to results reported in [28], which show that a feedforward configuration with two hidden layers of 18 and 16 nodes respectively is a convenient starting topology when six input measurements are available. A possible network overdimensioning due to this choice can be controlled by subsequent application of the pruning procedure. When using a lower number of radar channels, the NN topology simplifies correspondingly.

The training of the NNA has been carried out by feeding it with sets of vector pairs and modifying the weights of the connections to minimize the error function. The input vectors contain the simulated radar measurements, while the output vectors contain the quantity to be retrieved from them. In this case, the input is a set of six simulated σ^0 values (σ^0_{hh}, σ^0_{vv}, σ^0_{hv} at both L- and P-band), and the output is the value of the corresponding biomass.

Minimization of the error function has been pursued by a scaled conjugate gradient (SCG) algorithm [35]. This is a member of the class of conjugate gradient methods, general-purpose second-order techniques that help to minimize goal functions of several variables. Second-order indicates that such methods use the second derivatives of the error function, while a first-order technique, like standard backpropagation, only uses the first derivatives.

To determine when the training had to be stopped, we applied the "early stopping" procedure [36, ch. 9]. The performance of the net during the learning phase was monitored simultaneously both on the training and on the test set. For the training set, the overall error keeps on decreasing with increasing epochs, approaching a limiting value. Conversely, the error on the test set reaches a minimum value, after which it starts increasing if we continue the training. Once reached this minimum, the learning phase was interrupted.

B. Generation of Simulated Data

The training of the NNA, as well as the computation of the coefficients of the regressions used for comparison, need a sufficiently wide ensemble of coupled input–output data. However, radar measurements and, especially, the corresponding ground truth may be quite expensive to obtain over a statistically significant range of cases. Hence, the perspective of using theoretical models of backscattering in the processes of training and testing retrieval algorithms is an appealing one. A main problem lies in the accuracy with which a model is able to reproduce the measurements. Two limits are apparent. First, electromagnetic computations make use of a number of approximations to cope with the complexity of the real vegetation. Second, the relevant information on the structural and biophysical characteristics of the stands to be simulated must be included. This is clearly unfeasible on a global basis, but can be attempted only for relatively homogeneous types of vegetation, provided the relevant allometric information is available. In the following, we restrict ourselves to the case of conifers.

The generation of the sets of training vector pairs is carried out by using the vegetation scattering model developed at Tor Vergata [33], in conjunction with relevant relationships among the various components of a pine forest [37]. With reference to a six-input NNA, the model computes backscattering at hh, hv, and vv polarizations for L- and P-bands from ground data. Each σ^0 vector coupled to the corresponding biomass value trains the net. Here, our purpose is to investigate on the expected performances of NNAs when dealing with noisy radar data. As outlined above, noise can be of *natural* origin or due to the radar system. We have selected the soil moisture content and the understory biomass density among the many natural factors that affect backscattering measurements, while speckle has been considered as a significant originator of system noise. We point out that actual measurement perturbations stem from the various and numerous sources altogether. However, separately considering the effect of the three chosen parameters makes the analysis much more manageable.

Sets of data corrupted by natural and system noise have been generated as follows.

Different stands with 171 values of dry above-ground biomass, varying from 1 $\mathrm{kg \cdot m^{-2}}$ (roughly corresponding to 25 $\mathrm{m^3/ha}$) to 18 $\mathrm{kg \cdot m^{-2}}$ ($\sim$ 450 $\mathrm{m^3/ha}$) with step 0.1 $\mathrm{kg \cdot m^{-2}}$, have been assumed for our ensemble of simulated conifer forests. The reference value assigned to SMC is 20% by weight. Then, to reproduce the natural variability of soil humidity, two different sets of 20 random SMC values have been generated with Gaussian distributions, both centered on the nominal 20% value. The two sets are characterized by two different standard deviations, a small one, i.e., $\sigma_{\mathrm{smc1}} = 1\%$ by weight and a large one, i.e., $\sigma_{\mathrm{smc2}} = 10\%$ by weight. For each SMC value, the forest backscattering coefficients have been computed for each biomass, at hh, hv, and vv polarizations for both L- and P-bands. The obtained sets of 3420 σ^0 vectors form two statistical ensembles to be used to train the NNA. A second pair of 3420 σ^0 vector sets, obtained by other independent random SMC generations with the same average and standard deviations as the training sets, forms the NNA evaluation sets. An analogous procedure has been followed to generate training and evaluation sets of σ^0, assumed perturbed by fluctuations of the understory biomass density. The reference value assigned to UBD is 1.5 $\mathrm{kg \cdot m^{-2}}$ and the Gaussian distributions have standard deviations $\sigma_{\mathrm{ubd1}} = 0.05\ \mathrm{kg \cdot m^{-2}}$ and $\sigma_{\mathrm{ubd2}} = 0.5\ \mathrm{kg \cdot m^{-2}}$, respectively. Finally, the effect of speckle, representative of the system noise, has been taken into account by the following procedure. The backscattering coefficients of the forest stands, assumed homogeneous and untextured, have been computed for each value of biomass and for the reference values of SMC and UBD. Then, for each of the 1026 σ^0 we generated a random process having mean value equal to that σ^0 and obeying a corresponding gamma distribution [38]. Each distribution has been characterized by a value of the order parameter L in the range 1–1024, chosen to simulate measurements spanning from the quite noisy single-look observations to the relatively stable ones, as is the case when the σ^0's are averaged over the many pixels of a large stand.

TABLE I

ERROR RMS (KILOGRAMS PER SQUARE METER) OF BIOMASS OF SIMULATED CONIFER STANDS WITH VARIABLE SMC RETRIEVED BY LR AND NN ALGORITHMS FROM SETS OF σ^0 AT P-BAND, L- BAND, OR BOTH. (TOP LINE) ALGORITHMS TRAINED WITH LOW SMC VARIABILITY AND TESTED WITH SAME LOW SMC VARIABILITY. (SECOND LINE) BOTH TRAINING AND TEST WITH HIGH SMC VARIABILITY. (BOTTOM LINE) TRAINING WITH LOW, TEST WITH HIGH SMC VARIABILITY

P		L		P + L			
LR	NN	LR	NN	LR	NN	train	test
1.25	0.03	0.49	0.04	0.33	0.03	1%	1%
1.81	0.06	0.56	0.07	0.56	0.03	10%	10%
2.18	0.37	1.28	0.39	1.16	0.28	1%	10%

TABLE II

ERROR RMS (KILOGRAMS PER SQUARE METER) OF BIOMASS OF SIMULATED CONIFER STANDS WITH VARIABLE UBD RETRIEVED BY LR AND NN ALGORITHMS FROM SETS OF σ^0 AT P-BAND, L- BAND, OR BOTH. (TOP LINE) ALGORITHMS TRAINED WITH LOW UBD VARIABILITY AND TESTED WITH SAME LOW UBD VARIABILITY. (SECOND LINE) BOTH TRAINING AND TEST WITH HIGH UBD VARIABILITY. (BOTTOM LINE) TRAINING WITH LOW, TEST WITH HIGH UBD VARIABILITY

P		L		P + L			
LR	NN	LR	NN	LR	NN	train	test
0.57	0.02	0.74	0.02	0.55	0.02	0.05	0.05
1.20	0.04	2.57	0.07	0.73	0.04	0.50	0.50
1.60	0.30	2.17	0.63	2.00	0.17	0.05	0.50

C. Tests on NNA Robustness

Our discussion on the potential capability of the NNAs in retrieving biomass from backscattering measurement corrupted by natural noise is based on the simulated performance of the algorithms either properly or incorrectly trained, while the case of system noise is examined by feeding the net with three different levels of speckle. Moreover, we analyze the NNA performances for different availability of radar channels, i.e., we assume that three different sets of σ^0 measurements are available: either σ^0_{hh}, σ^0_{hv}, and σ^0_{vv} at either L- or P-band, or all σ^0 at both bands. In these cases, the algorithms are both trained and evaluated by sets of three- and six-component σ^0 vectors as input, and corresponding biomass as output. To assess the possible improvements of neural network algorithms over more standard retrieval schemes, the performance of linear regressions between the logarithm of the biomass and the backscattering coefficients in decibels [4], [39] has been evaluated and used as a benchmark. To this end, the regression coefficients have been computed from the same input/output datasets used for training the corresponding NNAs, and the evaluation has been carried out on the same NNA test set.

In the first study we simulate conifer forest stands whose underlying soil has a variable moisture content, due, for instance, to meteorological, seasonal, or climatic effects. Three cases are considered.

- SMC has small variability (standard deviation 1% by weight);
- SMC has large variability (standard deviation 10% by weight);

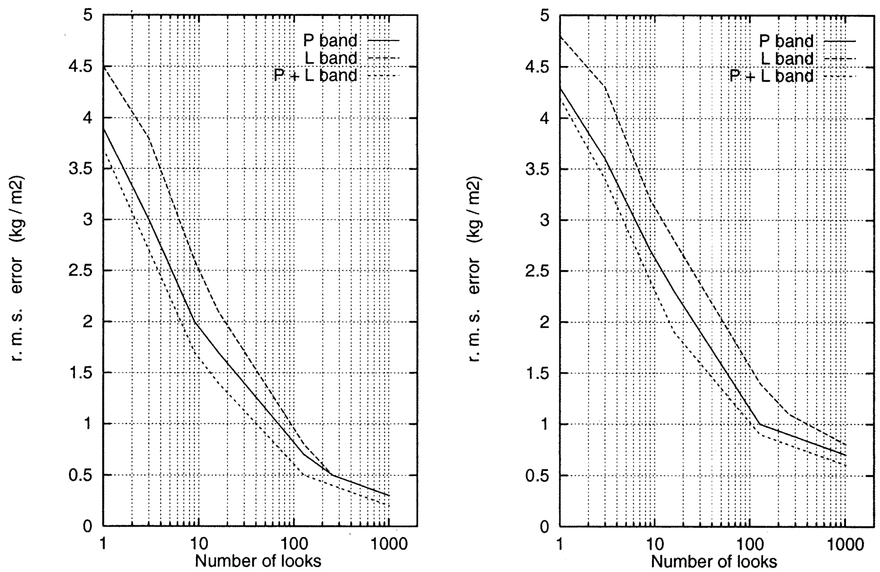

Fig. 1. Error rms ($kg \cdot m^{-2}$) of biomass of simulated conifer stands retrieved by (left) neural network and (right) linear regression algorithms from sets of speckle-affected σ^0 at P-band, L- band, or both, versus parameter L of speckle gamma distribution.

- SMC has indeed a large variability (10%, as before), but the algorithms have been incorrectly trained for the small (1%) variability case.

Table I compares the retrieval rms errors produced by a linear regression algorithm (LRA) with those originated by a neural net (NN) for the three aforementioned cases. Some points are worth to highlight. When trained properly, the accuracy of the NNA is generally better than that of a LR by more than one order of magnitude. In case of incorrect training, a NNA still performs considerably better than an LRA. The availability of copolar and cross-polar measurements at both L- and P-band leads to the best performance in the retrieval, especially for NNAs operating on noisy data. A peculiar difference is shown by the two algorithms: when inverted by LRAs, L-band data lead to lower errors than P-band data. The opposite is true for NNAs. We put forward the following explanation. The natural noise we are simulating consists in fluctuations of soil conditions. P-band is more sensitive than L-band to this kind of deviation from the nominal measurement conditions, due to its enhanced penetration through the vegetation canopy. Hence, we expect that the retrieval from L-band data be more accurate than that from P-band, were this type of noise the only source of error. However, being the sensitivity of L-band to forest biomass lower than that of P-band, this effect may be counterbalanced. Radar sensitivity, commonly intended as variation of backscattering for a given variation of the sought parameter, is not always adequate to predict the retrieval accuracy, since this latter does depend on the retrieval algorithm, especially when multiple inputs are used. In fact, in this case, if we inspect the retrieved values in different ranges of biomass (such results are not reported here for the sake of conciseness) we note that at high biomass the performance of both algorithms degrades more at L- than at P-band, but the LRA suffers considerably more than the NNA. The result is that the higher sensitivity of P-band measurements to arboreous biomass is better exploited by the NNA, thus succeeding in counterbalancing the effect of the varying soil moisture.

This simulation suggests that a neural network algorithm may be more robust than a linear regression with respect to soil moisture variations in retrieving forest biomass.

An analogous study has been carried out to investigate the performance of NNAs when, for given forest stands, the conditions of the understory are different, thus changing the relative contributions to scattering and attenuation mechanisms. Again, three cases are considered.

- UBD has small variability (standard deviation 0.05 $kg \cdot m^{-2}$).
- UBD has large variability (standard deviation 0.5 $kg \cdot m^{-2}$).
- UBD has indeed a large variability (0.5 $kg \cdot m^{-2}$, as before), but the algorithms have been incorrectly trained for the small (0.05 $kg \cdot m^{-2}$) variability case.

The rms retrieval errors reported in Table II show a pattern rather consistent with those obtained in case of SMC variations, although the natural noise has now a different origin. When trained properly, the accuracy of the NNA is generally better than that of the LR by more than one order of magnitude. In case of incorrect training, a neural net still performs considerably better than a linear regression. The availability of copolar and cross-polar measurements at both L- and P-band leads to the best performance in the retrieval, while both algorithms perform better on P-band measurements.

The third simulation regards the effect of speckle, which, together with thermal and calibration errors, is a source of measurement noise. LR and NN algorithms, trained with a speckle-affected dataset, have inverted another independently generated set. Both sets are characterized by the same levels of multiplicative noise, assumed uncorrelated between different channels.

The results, summarized in Fig. 1, indicate that, again, the retrieval by a neural net appears more accurate than the one by a linear regression. Using six measurements, at both L- and P-band, yields the higher accuracy, P-band remaining superior to L-band in case of a single-frequency three-polarization system. As expected, the diagrams point out the need of averaging the measurements over a sufficiently large area, e.g.,

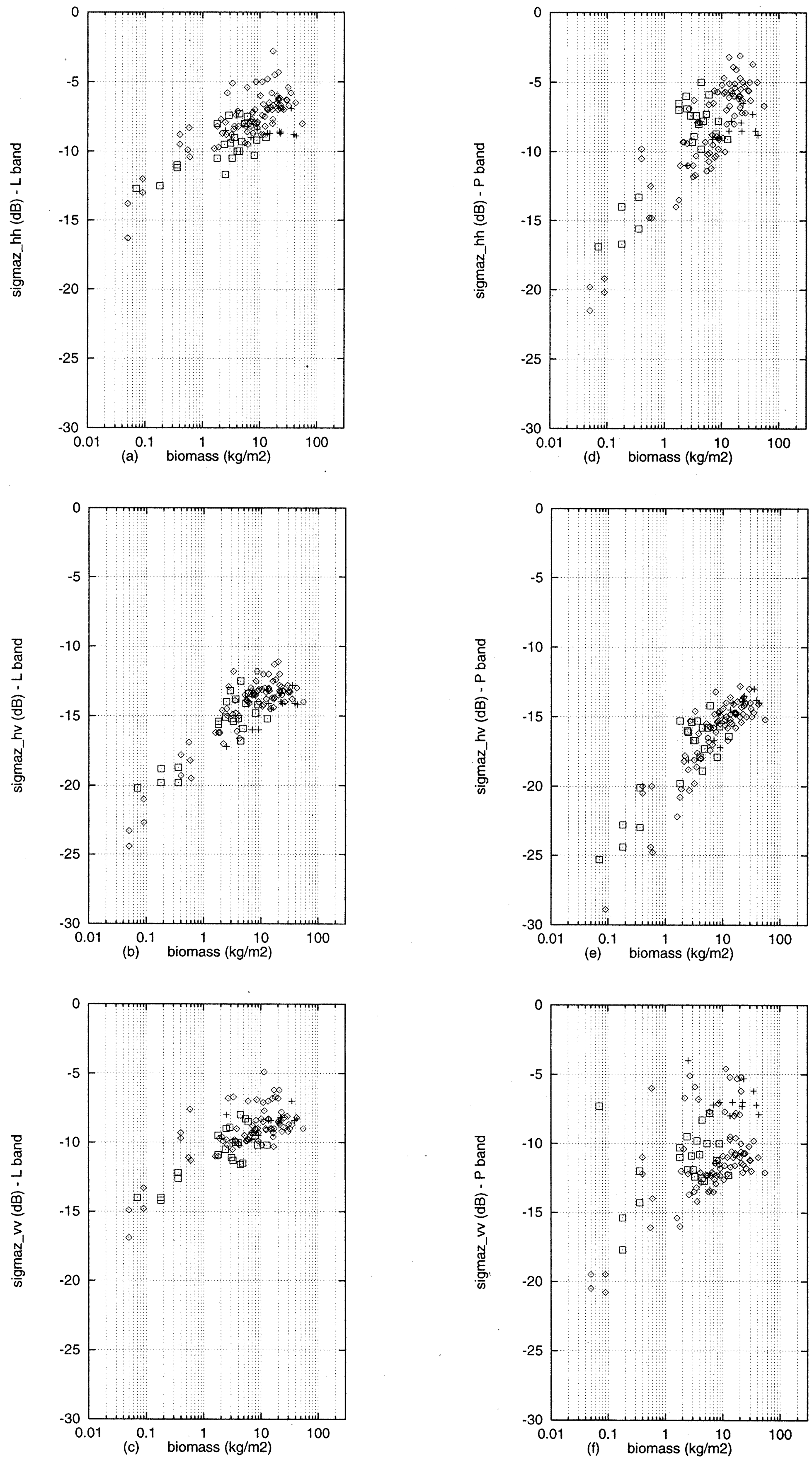

Fig. 2. Backscattering coefficients versus biomass taken from plots published in [5], [6], [23], and [40]. (Left) L-band, (right) P-band, (top) σ^0_{hh}, (middle) σ^0_{hv}, (bottom) σ^0_{vv}. (Diamonds) Conifer stands. (Squares) Poplar. (Crosses) Mangrove.

of the order of 1 ha for the AirSAR, to attain an acceptable accuracy. Indeed, any retrieval algorithm normally uses values computed over forest stands including many pixels.

As a concluding remark, we point out that the above results for simulated data have been obtained by a neural net in its basic configuration. The optimization of the NN topology, as described in the following Section III-B, is expected to further improve the performance of the algorithm.

III. Test on Experimental Data

The indications deduced from the above results, albeit probably useful, are still based on simulations and regard the effects of a small number of parameters out of the many that may enter into play. The question on what can be expected by a single NNA when operating on global real-world data remains open. To try to give an answer, we have used NNAs to retrieve the biomass of a set of different forests from actual radar measurements. The general frame of this analysis is the same as in the previous section, with input data formed by copolar and cross-polar measurements at L- and P-band. The performance of the NNA is now compared against those of both linear and nonlinear regressions, and also of a model-based retrieval procedure.

A main difficulty encountered in this kind of study is the scarcity of data, and in particular of ground measurements, that can be found in literature. Even if all available data are joined together and some suitable strategy is implemented, this poses an obvious limit to the statistical significance of the conclusions.

A. Experimental Dataset

We searched the open literature for published L- and P-band multipolarization forest backscattering coefficients accompanied by corresponding ground truth measurements. The radar data we found are stand-averaged σ^0's obtained by the NASA/JPL AirSAR in the course of different campaigns over five different geographic locations. The sets of data refer to the following:

- Landes forest near Bordeaux, France, collected on August 16, 1989 [5];
- Horsterwold forested area in The Netherlands, collected in August 1989 [6];
- Duke University forest near Durham, NC, collected on September 2, 1989 [5];
- Bonanza Creek experimental forest in the proximity of Fairbanks, AK, collected on May 6, 1991 [23];
- coastal tropical mangrove forest in French Guyana, collected on June 11, 1993 [40].

Hence, the radar measurements we assembled refer to different types of forest in diverse climatic conditions. The Landes forest contains plantations of maritime pine; the Horsterwold data refer to poplar stands; the Duke forest has naturally grown loblolly pine; the Bonanza Creek forest is a natural one of white and black spruce, with eventual contamination by other species (mainly balsam poplar, alder, and birch); and the Guyana forest is a uniform evergreen mangrove forest. Most data refer to flat areas or relatively low topographic relief, with a local incidence angle in the range 35° to 50°. The considered radar acquisitions were accompanied by ground data collection, which provide the biophysical characterization of the measured stands, including, in particular, either the total above-ground dry biomass, or, in one case, the bole volume. Since the trunk densities are dependent on tree age and difficult to estimate [6], in this latter case, we evaluated the biomass per unit area ($\mathrm{kg} \cdot \mathrm{m}^{-2}$) of the poplar stands by simply multiplying the volume per unit area ($\mathrm{m}^3 \cdot \mathrm{ha}^{-1}$) by 0.04, which is a suitable factor according to our experience. From the above published data, we selected 108 input-output experimental σ^0-biomass vector pairs with this latter (output value) in the range 0.05 (clear-cut) to 30 $\mathrm{kg} \cdot \mathrm{m}^{-2}$. Note that care was exerted to include all dispersed values, to be on the pessimistic side. The assembled input backscattering coefficients σ^0_{hh}, σ^0_{hv}, and σ^0_{vv} at L- and P-band are shown in Fig. 2(a)–(f). As expected, the dispersion of σ^0 values for the same or close nominal values of biomass is apparent, especially at P-band and for copolarization (vv, in particular). This behavior stems from several factors. First of all, it is well known that the relationship between biomass and backscatter is nonunique, since this latter is affected by the structural and dielectric properties of soil and stands, as stressed by [11]. An additional reason lies in the incidence angle being not the same (a variation of the order of 1–2 dB is typical for a variation of 10° of the incidence angle [23], [41]). Moreover, since we simply extracted the data from published diagrams, errors in reading can be present, although we discarded potentially ambiguous values. In absence of accidental oversights (we assume published plots exempt from flaws), we estimate our reading error below 1 dB. Finally, major sources of error reside in the processes of measuring biomass and σ^0. Experimenters report uncertainties in the biomass (or bole volume) evaluation of 10% to 15% [5], [6], [40], rising to about 30% in one case [23]. As far as backscattering is concerned, all considered data were obtained by the same AirSAR system; hence, the whole set is homogeneous from the point of view of the measurement device, and the absolute radiometric calibration is expected to be of the same order for all data. Indeed, when the experimenters followed the POLCAL procedure [42], nominal calibration uncertainty is estimated about ± 1.9 and ± 1.2 dB at P- and L-band, respectively [43]. The reported characterization of errors in biomass measurements and radar calibration, the use of the same SAR system, and the averaging of σ^0 over whole stands should lead to a relatively homogeneous data population. Nevertheless, some unforeseen error could still be present, as observed in the σ^0 acquired by the AirSAR over the Thetford Forest (U.K.) in 1989 [44], which prevented us from including these data into our analysis, in spite of the completeness of the corresponding detailed ground survey [45]. Probably this is not the case here, since the data assembled in Fig. 2(a)–(f), after all appear statistically homogeneous.

We stress that the purpose of this section is to assess if a single neural net algorithm can be meaningfully used to retrieve biomass on a global scale, i.e., without having to adapt the algorithm to each particular biome and vegetation feature.

B. Biomass Retrieval Results

The adopted configuration, training, and test procedures of the NNAs are basically the same as in Section II-A. However, an optimization of the net has been carried out before applying it to the data inversion.

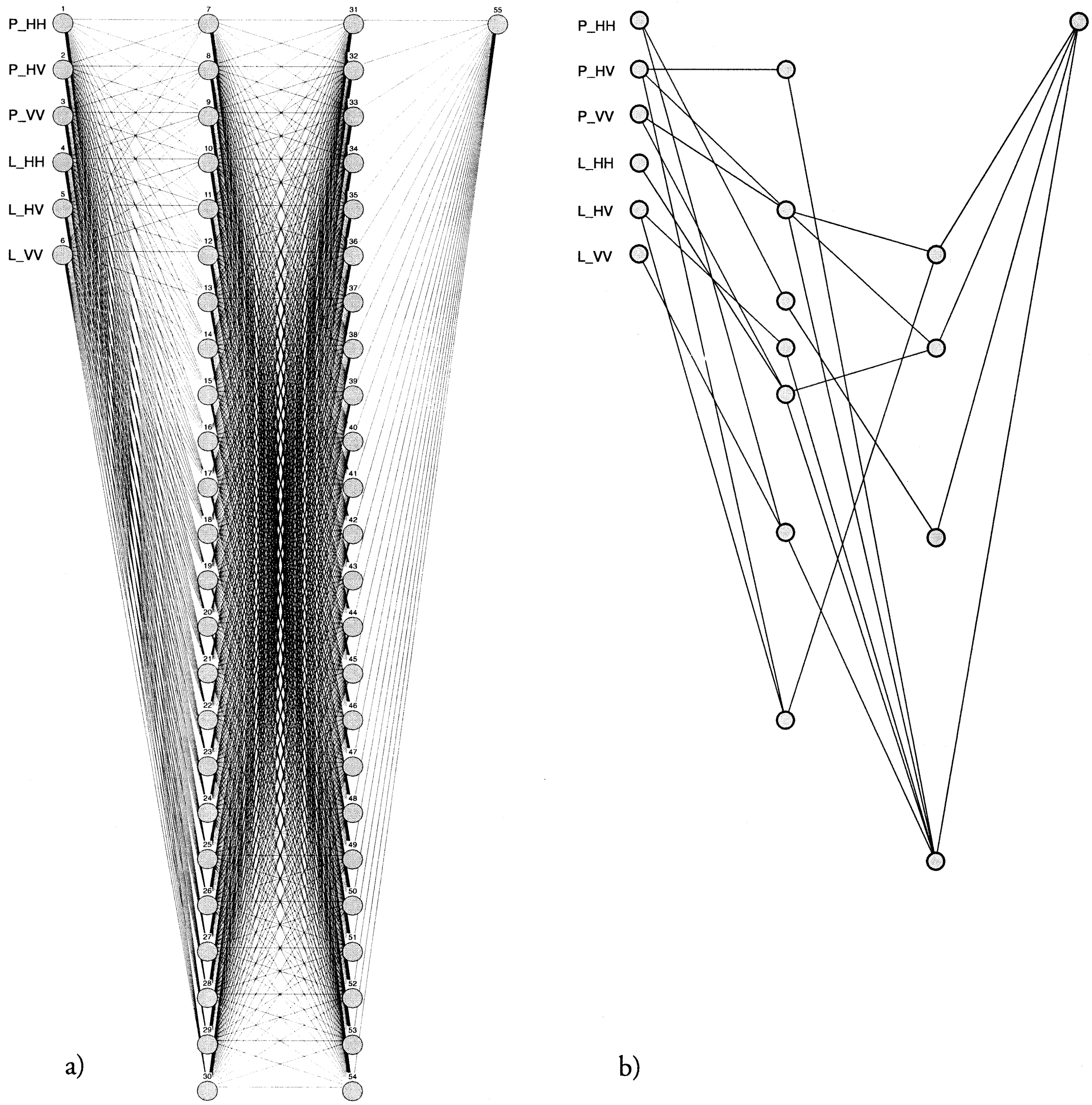

Fig. 3. Six-input neural network. (Left) Initial. (Right) pruned.

The initial topology of the network has been simplified by a pruning strategy which removes the ineffective connections and units. To this end, the connection with the minimum weight (in magnitude) in the initial configuration has been cut off and the new network retrained for as many epochs as required by the early stopping procedure. The same routine has then been applied to the new configuration, the procedure of sequential pruning and training being repeated for several cycles, until further removal of connections resulted in an evident increase of the retrieval error. In the course of the pruning process, the changes of the weights were small when a weak connection was removed, rising with the strength of this latter. The absolute values of the weights gradually increased with the decreasing number of connections, following the concentration of the associative memory distributed among the elements of the net. The weights were observed to have varied by one order of magnitude between the initial full net, with hundreds of elements, and the final pruned net, with tens of elements.

With reference to the six-input configuration, reinitializing and retraining the final net (details on the procedure are reported in [46]) allowed us to attain an rms error almost 10% lower than the one for the initial topology. Hence, the outcome of pruning has been a slight improvement of the retrieval accuracy, in addition to a considerable reduction (25 connections against 744) of the number of neurons, hence of the computational effort. A comparison between the initial topology of our six-input network and the one optimized by pruning is shown in Fig. 3. The optimized algorithm has then been tested in the retrieval exercise.

We subdivided the 108 input (σ^0 measurements) and output (biomass) vectors into three equal subsets, distributed rather uniformly in biomass, two of which, joined together, trained the optimized NNA in turn, thus yielding three sets of weights for the net. The NNA with each weight configuration was used to retrieve the biomass from the 36 remaining σ^0 vectors, according to the training and testing cross-validation strategy reported in

TABLE III
ERROR RMS (KILOGRAMS PER SQUARE METER) OF BIOMASS RETRIEVED BY NN, LR, NLR ALGORITHMS FROM VARIOUS SETS (P-BAND ONLY, L-BAND ONLY, BOTH BANDS) OF EXPERIMENTAL $\sigma^0_{\rm hh}$, $\sigma^0_{\rm hv}$, AND $\sigma^0_{\rm vv}$

P			L			P + L		
LR	NLR	NN	LR	NLR	NN	LR	NLR	NN
5.2	5.2	4.4	8.1	5.9	5.1	5.5	5.5	4.3

[47, ch. 9]. This strategy results into three retrieval exercises for which each of the three test patterns is independent from the corresponding training sets. The overall 108 test patterns are probably still a too small number to form a fully significant statistical set. Nevertheless, some consistent behavior can be identified from the obtained figures.

Table III reports the rms retrieval errors when multipolarization ($\sigma^0_{\rm hh}$, $\sigma^0_{\rm hv}$, and $\sigma^0_{\rm vv}$) measurements at either L- or P-band are used, and compares the results with those obtained by simultaneously using the σ^0's at both bands. The results in the table indicate that the neural net algorithm retrieves biomass from actual measurements better than both linear and nonlinear regression do and that P-band data yield a lower error. The availability of measurements at both L- and P-band leads to the best performance, with an rms error equal to the 57% of the dispersion of the biomass test data. It should be noted that, instead, the six-input LR algorithm yields a degraded estimate with respect to the P-band three-channel LRA. Probably, this effect is only partly related to the nonlinearity of the problem. Rather, it may indicate that the more sophisticated processing accomplished by the neural network is able to make use of the pieces of independent information contained in the measurements, whereas the regression algorithms suffer more from the noise and saturation in the added L-band data than benefit from the additional embedded information [48]. Fig. 4(a)–(c) allows a visual comparison among the retrievals (by the optimized NN algorithm) from L-, P-, and L- + P-band data, respectively. The correlation coefficients for the three retrievals are $\rho = 0.77$, $\rho = 0.84$, and $\rho = 0.84$, respectively. These figures are higher than the ones relative to the retrievals by LRAs, i.e., $\rho = 0.49$ $\rho = 0.74$, and $\rho = 0.70$, respectively (plots are not shown here). It is interesting to appreciate how the biomass of the mangrove stands is fairly well retrieved up to about 25 kg $\cdot$ m^{-2}, in spite of their quite peculiar structure. The results obtained by nonlinear regressions deserve some comments. When inverting either P- or P- plus L-band data, a second-order algorithm does not yield any improvement on the linear one, while the error for the third-order regression is 4% higher. When inverting L-band data, which saturate earlier with increasing biomass, a third-order regression performs better (8%) than the second-order, but the fourth-order algorithm is worse (the error is 12% higher). These results are consistent with the observation [50, ch. 1] that the ability of a polynomial to represent additional noisy data reaches an optimum for a relatively small order. Anyhow, even when the nonlinear regression gives more accurate results than the linear one, the error is still higher than that given by the neural network algorithm. This may indicate that the NN approach can be more than yet another nonlinear regression technique.

As noted before, extensive measurement sets to use for training are expensive to obtain. Hence, the possibility of using theoretical models of backscattering in the training process is appealing, since a variety of measurement conditions, scattering features, and system noise can be simulated to teach the retrieval algorithm to cope with the natural complexity of observations. The main question at issue is how much the obvious accuracy limits of a model is going to affect the performance of an algorithm inverting real measurements.

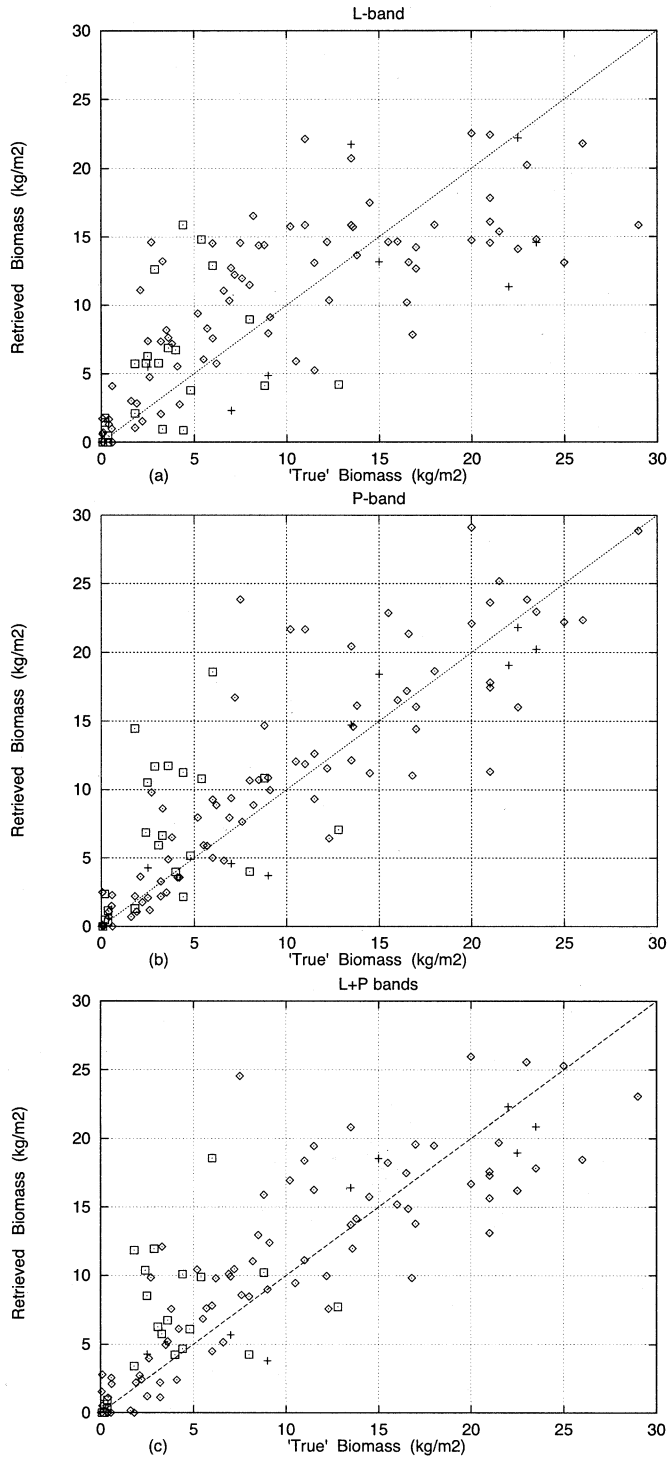

Fig. 4. Biomass (kg $\cdot$ m^{-2}) retrieved by NNAs trained with experimental data versus "true" biomass from channels. (a) $\sigma^0_{\rm hh}$, $\sigma^0_{\rm hv}$, and $\sigma^0_{\rm vv}$ at L-band. (b) $\sigma^0_{\rm hh}$, $\sigma^0_{\rm hv}$, and $\sigma^0_{\rm vv}$ at P-band. (c) $\sigma^0_{\rm hh}$, $\sigma^0_{\rm hv}$, and $\sigma^0_{\rm vv}$ at both L- and P-band. (Diamonds) Conifer stands. (Squares) Poplar. (Crosses) Mangrove.

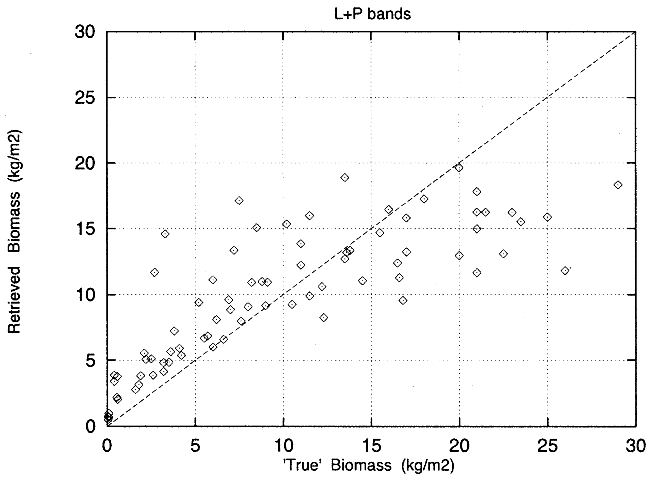

Fig. 5. Biomass ($kg \cdot m^{-2}$, conifers only) retrieved by a six-input NNA trained with theoretical simulations versus "true" biomass from σ^0_{hh}, σ^0_{hv}, and σ^0_{vv} data at both L- and P-band.

To investigate on the possibility of a theoretical training of the neural retrieval algorithm, we restricted ourselves to the case of conifers for which a model is available to us. The optimized six-input NNA was trained by a set of L- and P-band backscattering data simulated by the already mentioned vegetation scattering model [33] and tested on the subset of experimental σ^0's that were available for 77 conifer stands. Fig. 5 shows the results obtained by the model-trained six-input NNA, which yields a retrieval rms error of 4.6 $kg \cdot m^{-2}$, i.e., slightly higher than the one of the algorithm trained by the experimental data and inverting the full set of measurements. The correlation coefficient $\rho = 0.81$ is now correspondingly lower.

The availability of simulated backscattering coefficients makes readily feasible a model-based retrieval exercise for the same 77 conifer stands. To estimate the biomass of each stand, we carried on an iterative procedure that minimized the least square difference between measured σ^0's and those simulated by the scattering model [33], already used to train the neural net. The biomass retrieved by this method is affected by an rms error of 6.1 $kg \cdot m^{-2}$, i.e., 30% higher than the one yielded by the NNA, trained by the same set of theoretical values and applied on the same set of experimental data. The correlation coefficient $\rho = 0.64$ is consistently lower.

C. NN-Based Sensitivity Analysis

The previous results give some hints on how a neural network algorithm is expected to perform in the presence of natural variability or system noise. An interesting addition is contributed by an extension of the NN pruning technique, which provides a rather peculiar and straightforward method to examine which frequency and polarization, in the chosen context, contain less information on the biomass and, conversely, which are the channels crucial for the success of retrieval. This issue has been addressed by several previous studies, prevalently on the basis of the radar sensitivity, i.e., of the increment of backscattering for a given change of biomass of given types of vegetation. However, as already outlined in Section II-C, it is not obvious that the results are independent from both the retrieval algorithm and the set of measurement data that were used. To analyze the sensitivity from another point of view, including the algorithm, we considered the six-input neural network trained by the experimental data and prolonged the pruning procedure to the input layer, until five of the six components of the input vector were removed (we remind that an input or hidden unit is removed when it has lost all its connections). The result of this analysis is synthetically reported in Table IV, where we specify the order of removal of the input radar channels, which is inversely related to the order of importance of these later. We point out that some researchers are wary of neural networks, often regarded as black-boxes mainly because their internal dynamics remains scarcely accessible. This is indeed the case, but the above results suggest that appropriate procedures can extract physical information from an otherwise "blind" algorithm [49]. Here, the NNA subjected to a prolonged pruning yields conclusions consistent with previous theoretical and experimental findings [1], [5], [51], i.e., the cross-polarized backscattering coefficients are identified as the most important for the retrieval, P-band being more sensitive than L-band.

TABLE IV
RATING OF RADAR CHANNELS DEDUCED FROM THE ORDER OF REMOVAL OF UNITS IN THE INPUT LAYER OF THE NETWORK

Rating	Band	Polarization
1	P	hv
2	L	hv
3	L	hh
4	L	vv
5	P	vv
6	P	hh

It is clear that the results reported in this section were obtained from a relatively narrow ensemble of experimental data, mainly referring to conifers. The availability of richer sets of calibrated radar measurement, together with the corresponding ground data, is highly desirable to reach possibly sounder conclusions.

IV. CONCLUSION

This study concerns the application of neural network algorithms to the retrieval of forest stand biomass from copolar and cross-polar backscattering coefficients at both P- and L-band. The use of NNAs has been considered in three situations, i.e., trained on model data to invert model values, trained on real data to invert actual measurements, and trained on simulated data to invert measured data. Simulations of selected natural and system noise provided the means to critically appreciate the robustness of the NNAs, with linear (after logarithmic transformations) regressions regarded as benchmark. An assembly of AirSAR data published in the open literature has yielded training and evaluation sets for assessing the expected performance of the algorithms when operating on real radar measurements, eventually taken over diverse forest types, as may be the case when global biomass monitoring is under consideration. A comparison between the NNAs and both linear and nonlinear regression algorithms points out the overall superior performance of the neural algorithm. Indeed, the mapping of the multidimensional input (three or six σ^0's) onto the biomass value is highly nonlinear and difficult to retrieve, so that a properly designed and trained NN is a valuable tool to implement this mapping. The neural network was made as simple (and fast) as possible by means of a fast learning (SCG) scheme and of a pruning procedure, which, beside reducing by more than 95% the number of the initial network connections, yielded an algorithm more precise, hence with improved generalization properties. It has also been shown how extending the pruning to the input layer can yield a method for appreciating the information content of the individual radar channels in a fast and straightforward manner. Finally, the use of an electromagnetic model in training the NNA has been considered for the case of conifers. In this case, the NN retrieval accuracy compares favorably also with that of a model-based procedure. The skepticism sometimes manifested on the ability of wave scattering models to reproduce backscattering from forests is quite reasonable. In fact, we experienced that in some case a model with carefully selected inputs, e.g., taking into account the links among several forest stand parameters (such as trunk density, height, and diameters) related to the botanical growth processes, simulates measurements with an accuracy sufficient to be serviceable. Efforts for broadening the range of applicability of models are of great worth, since successfully employing theoretical data in training the net would definitely augment the generalization properties of neural algorithms, hence their potential in global-scale retrieval.

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