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Neural-network approach to ground-based passive microwave estimation of precipitation intensity and extinction

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Summary A physically-based passive microwave technique is proposed to estimate precipitation intensity and extinction from ground. Multi-frequency radiometric measurements are inverted to retrieve surface rain rate, columnar precipitation contents and rainfall microwave extinction. A new inversion methodology, based on an artificial neural-network feed-forward algorithm, is evaluated and compared against a previously developed regression technique. Both retrieval techniques are trained by numerical simulations of a radiative transfer model applied to microphysically-consistent precipitating cloud structures. Cloud microphysics is characterized by using parameterized hydrometeor drop size distribution, spherical particle shape and dielectric composition. The radiative transfer equation is solved for plane-parallel seven-layer structures, including liquid, melted, and ice spherical hydrometeors. The proposed neural-network inversion technique is tested and compared with the regression algorithm on synthetic data in order to understand their potential and to select the best frequency set for rainfall rate, columnar contents and extinction estimation. Available ground-based radiometric measurements at 13.0, 23.8, and 31.6 GHz are used for experimentally testing and comparing the neural-network retrieval algorithm. Comparison with rain gauge data and rain extinction measurements, derived from three satellite beacon channels at 18.7, 39.6, and 49.5 GHz acquired at Pomezia (Rome, Italy), are performed and discussed for a selected case of light-to-moderate rainfall.

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Introduction

Quantitative estimate of rainfall is a key parameter within meteorological and hydro-geological applications (Houze, 1982). Rainfall forecast can be potentially improved by assimilating rain measured fields into numerical weather prediction (e.g., Marécal and Mahfouf, 2000; Bauer et al., 2002). Runoff and storm-flow response models are critically dependent on the knowledge of accumulated rainfall within a catchment (e.g., Orlandini et al., 1999). The extreme variability of precipitation in time and space translates into a cumbersome approach to its retrieval since all techniques show their potentialities and limitations within respect to meteorological and hydro-geological input requests.

Rain gauge network represents a valuable technique to gather information about accumulated on a given area, even though their sparse and point distribution poses problems of spatial interpolation and downscaling (e.g., Lebel et al., 1987; Deidda et al., 1999). Temporal data can be collected with a sampling of the order of minutes and can be degraded by wind effects. Together with their relative low cost, most importantly the operational aspects related to the management of rain gauge network has been nowadays highly simplified due to the flexibility of mobile remote inter-connections. Rain disdrometers can represent a valid, yet costly, alternative to rain gauges with the advantage to provide information on the raindrop size distribution as well.

Another consolidated technique for rainfall monitoring is the use of volume data collected by weather Doppler radar either at S or C band (e.g., Marzano et al., 1994; Borga et al., 2000). Microwave weather radars can provide a three-dimensional picture of the rainfall with an overall resolution of the order of hundreds of meters, since transverse volume resolution increases with the square of the range, while range resolution depends only on the pulse length. Radar volume data can be generally acquired within few minutes. Radar data processing is not an easy task to be accomplished, since instrumental calibration, ground-clutter, beam blockage, rainfall spatial gradients can significantly affect the estimate of rain rate field (Ciach and Krajewski, 1999). Moreover, at C band strong two-way path extinction can cause a decrease of the receive power thus implying an underestimation of heavy rainfall intensity within a given range bin (Aydin et al., 1989). The entire radar system often requires a conspicuous investment, a huge installation tower and a costly maintenance.

Finally, it should be mentioned that in the last decade spaceborne radiometric techniques have been successfully applied to the rainfall retrieval on a global scale (e.g., Petty, 1995; Pierdicca et al., 1996; d'Auria et al., 1998). Microwave radiometry has proved to be a fairly accurate tool, even though its major drawback is represented by the poor spatial resolution (i.e., order of tens of kilometers) and low temporal sampling (Tassa et al., 2003). The latter problem is related to the fact that microwave radiometers are installed aboard low-Earth-orbit (LEO) platforms which exhibits an overpass period of about 12 h. Synergies of more platforms, carrying microwave radiometers, and integration with infrared radiometers aboard geostationary-Earth-orbit platforms have been recently envisaged to overcome these limitations (Marzano et al., 2001). More recently, spaceborne microwave radars, installed aboard LEO platforms such the Tropical Rainfall measuring Mission (TRMM), have reinforced the essential role of satellite rain meteorology (e.g., Marzano et al., 1999a; Di Michele et al., 2003).

Ground-based microwave radiometry has been used since the late sixties (Westwater, 1993). Its major and established applications are related to the estimate of columnar water vapour content, columnar liquid water of non-raining clouds, temperature profiles and clear-air path attenuation (e.g., Westwater et al., 1990; Ciotti et al., 1995; Hornbostel and Schroth, 1995). The increasing use of multi-frequency radiometers in ground-based stations, especially for operational meteorology and satellite communication purposes, raises the question of their potential for also retrieving rainfall rate, columnar rain and ice contents and microwave rainfall extinction (Sheppard, 1996; Marzano et al., 1999c; Liu et al., 2001; Czekala et al., 2001; Marzano et al., 2002).

Microwave radiometry may offer several advantages with respect to the above mentioned techniques. With respect to rain gauges, it can give areal estimates of accumulated rainfall with a competitive temporal sampling (order of tens of seconds, depending on data integration time), together with an further information on ice content and extinction. With respect to weather radar, it is certainly less costly and fairly simple to maintain, being in many circumstances a portable sensor. On the contrary, microwave radiometers are not generally able to provide range-resolved profiles of rainfall, even though this information might be available at coarse resolution using sophisticated inversion techniques. A valuable product of microwave radiometry is the possibility to predict rain total extinction in a fairly accurate way, a feature which can be of relevant use for correcting radar data in presence of significant rain attenuation (Marzano et al., 1999a; Marzano and Bauer, 2001). The complementary nature of microwave radiometry and radar measurements for rainfall monitoring is, indeed, receiving more and more attention. With respect to spaceborne radiometer technique, ground-based radiometry can offer a tool to validate rain estimates together with rain gauges and weather radars. Indeed, a powerful perspective to improve the accuracy of rain quantification is to integrate all these sources (i.e., rain gauges, radar and radiometers) into one synergic scheme devoted to precipitation monitoring with high temporal and spatial resolution (e.g., Hogg, 1989; Boni et al., 1996).

When developing new retrieval methodologies, a crucial step is represented by the way in which the inverse problem is faced. On one hand, a pure empirical statistical approach would resort to the use of measurements of the parameters to be estimated and the observables (e.g., Liu et al., 2001). The main limitation of this approach is the lack of physical understanding of the problem and the impossibility to generalize the method to other sensor configurations. On the other hand, an alternative way of proceeding is develop a detailed forward model, based on the parameterization of precipitation microphysics and an electromagnetic model of sensor response (e.g., Marzano et al., 1999c; Czekala et al., 2001; Marzano et al., 2002). Furthermore, the inverse problem can be either treated as an optimization problem, requiring a fast forward model to be use in real-time for minimization purposes or as an estimation problem, where a relation between the unknowns and the observables is possibly formulated. Notice that, in the latter case, the relation can be still derived from a numerical forward model.

In this paper, a physically-oriented passive microwave technique, based on a neural-network approach, is proposed to estimate precipitation intensity and extinction from ground. A new inversion methodology, based an artificial neural-network feed-forward algorithm, is evaluated and compared against a previously-developed regression technique. Both retrieval techniques are trained by numerical simulations of a parameterized radiative transfer model, applied to microphysically-consistent precipitating cloud structure. The proposed inversion technique is tested and compared on synthetic data in order to understand their potential and to select the best frequency set for rainfall rate, columnar contents and extinction estimation. Available ground-based radiometric measurements at 13.0, 23.8, and 31.6 GHz are used for experimentally testing and comparing the neural-network retrieval algorithm. Comparison with rain gauge data and rain extinction measurements, derived from three satellite beacon channels at 18.7, 39.6, and 49.5 GHz acquired at Pomezia (Rome, Italy), are performed and discussed for a selected case of light-to-moderate rainfall.

Characterization of ground-based microwave radiometric observations of precipitation

The substantial lack of in situ cloud and precipitation data suggests tackling the forward, and consequently the inverse problem, by using a model-based approach. An advantage is the flexibility of the numerical framework in terms of model parameter tuning and variable sensor configurations. The major drawback is the representativeness of its microphysics and electromagnetic description which needs to be carefully adapted to a large variety of scenarios (e.g., Marzano and Bauer, 2001). The radiative transfer theory (RTT) offers a suitable theoretical model to characterize the down-welling brightness temperature, measured by a microwave radiometer and due to clouds and precipitation (Marzano et al., 1999b; Czekala et al., 2001; Smith et al., 2002). The rainfall radiative model, adopted in this paper, is here briefly summarized in order to give a physical understanding of the retrieval results. For further details we refer to the work of Marzano et al. (2002).

A plane-parallel geometry is assumed as a schematic model of a vertically-inhomogeneous precipitating cloud of total thickness H. Note that this assumption is not limiting the applicability of the model to ground-based passive measurements as the relatively narrow beamwidths of microwave radiometers ensure a fairly uniform cloud filling within the antenna field-of-view. The unpolarized azimuthally-symmetric down-welling brightness temperature $T_B(z=0,\theta)$, observed from ground ($z=0$) at a zenith angle θ and a frequency f, can be formally expressed by means of the integral form of the *radiative transfer equation* (RTE). A fundamental quantity within RTE is the zenith optical thickness τ, or extinction, at frequency f, expressed by:

$$\tau(0,z)=\int_0^z k_e(z')\,dz', \tag{1}$$

being z the vertical coordinate and k_e the extinction coefficient. A measure of the rainfall scattering efficiency is the volumetric albedo w (i.e., $w=k_s/k_e$ with k_s the scattering coefficient), while the angular scattering properties are described by the volumetric phase bistatic function p. It is worth noting that τ, w and p completely defines the single-scattering properties of a rainfall medium, but at microwaves precipitation-sized hydrometeors are such that, besides extinction and emission, multiple scattering phenomena cannot be neglected and must be taken into account by RTE for a quantitative evaluation of the microwave radiometric response (e.g., Smith et al., 2002).

In order to face the inverse problem in a physically-based statistical way, the RTE needs to be applied to precipitating cloud structures, specified with respect to geometrical, dielectric and microphysical properties. To accomplish this task and to ensure a physical consistency of hydrometeor vertical distributions, the numerical outputs of a three-dimensional time-dependent cloud mesoscale model have been used for generating the cloud-structure data set (Pierdicca et al., 1996; Marzano et al., 1999a). Cloud vertical profiles explicitly describe the detailed vertical distribution of four species of hydrometeors: cloud droplets, rain drops, graupel particles, and ice particles. The hydrometeors have been assumed to be spherical and characterized by inverse-exponential size distributions. Even though ice crystals are not spherical, for ground-based observations this assumption produces negligible differences in the contribution of the iced layer to the total brightness temperature. This is because of the high opacity of rain and graupel closer to the sensor. Notice that here we consider here the polarization signature as a second-order effect with respect to other phenomena (e.g., water films on antenna in Jacobson et al., 1986 and Marzano et al., 2002). Moreover, if a retrieval perspective is pursued, hydrometeor non-sphericity may introduce an appreciable bias if the alignment is not properly specified. In a way, the assumption of spherical drops represents a conservative choice.

The cloud structures have been vertically averaged to seven homogeneous layers in order to reduce the complexity of the microphysical description. After classifying the cloud structures into meteorological cloud genera the cloud data set has been extended by means of a Monte Carlo statistical procedure, based on the use of the mean vector and the correlation matrix of the hydrometeor contents. In this work we have considered both stratiform and convective clouds producing rain. As a result, a data set of several thousands of cloud structures has been statistically generated retaining the physical and statistical features of the input microphysical cloud model. Further details on the dielectric and microphysical characterization, including a rough melting layer model for stratiform rain, can be found in Marzano et al. (2002).

To associate T_B's to each cloud structure, a radiative transfer model, based on the fast and fairly accurate Eddington solution, has been used. Its accuracy for modeling the radiometric response of raining clouds has been recently shown in literature by Smith et al. (2002). Within each layer, the temperature has been assumed linearly dependent on the height, and the gaseous absorption has been computed by means of the Liebe model (Liebe, 1989). The land surface emission has been modeled by a Lambertian emissivity.

Thus, a cloud-radiative data set, consisting of cloud structures, related total extinctions and brightness temperatures at the chosen frequencies and observation angles, has been simulated.

The following figures illustrate the results of the radiative transfer simulation applied to the randomly-generated cloud data set for stratiform and convective rain. Here we refer to the rainfall extinction at 18.7, 39.6, and 49.5 GHz and to radiometric channel frequencies at 13.0, 23.8 and 31.6 GHz. This choice is suggested by the availability of measurements at these frequencies (see following sections), but it is not restrictive since the developed model is able to simulate any radiometric observation from 1 to 300 GHz.

As an example of synthetic model outputs, Fig. 1 shows the simulated brightness temperatures at an elevation angle of 41.8° for both 13.0 GHz and at 31.6 GHz channels as a function of surface rain rate. Stratiform and convective rainfall is considered. This choice of the observation angle refers to the experimental case discussed later on. Figs. 2 and 3 show the same as in Fig. 1, but with respect to the columnar equivalent water content (CEWC) of cloud and rain hydrometeors and with respect to the total extinction at 18.7 GHz.

As expected, the total extinction increases with frequency and T_B tends to saturate for high values of extinction at higher frequencies due to the large rainfall and graupel albedo. This behavior is more accentuate for convective rainfall than for stratiform due to the higher precipitation intensity. It is worth mentioning that the 13.0 GHz channel has almost a linear response to path extinction for stratiform rain due to the lower atmospheric opacity. It is noteworthy that T_B's are more correlated with rain CEWC and total extinction than with surface rain rate due to the inherent features of the radiometric slant-path observation.

Neural-network based retrieval of precipitation intensity and extinction

Previous figures prove that the faced inverse problem is strongly non-linear and characterized by a large dispersion, depending on the parameter to be retrieved (e.g., extinction appears strongly correlated to observed T_B's than surface rain rate). Any iterative approach based on the minimization of a proper RTE functional should tackle the issue to find a global minimum (i.e., to avoid local minima traps). Moreover, the latter approach would be computationally very intensive.

The cloud-radiative data set, described in the previous section, represents a valuable source to develop a statistical inversion algorithm. in this work a new neural-network based algorithms has been developed for different sets of radiometric channel frequencies. Artificial neural networks (NN) represent a very versatile and powerful tool to deal

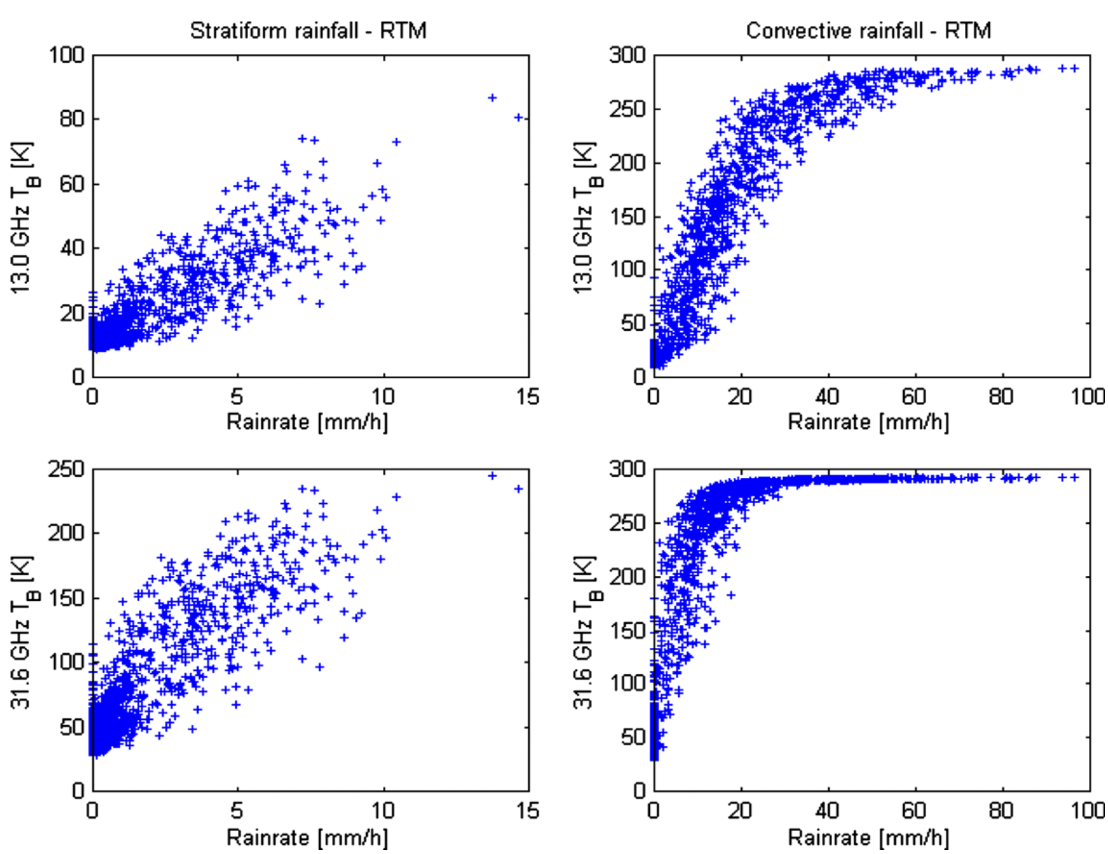

Figure 1 Brightness temperatures (T_B's), simulated by means of a radiative transfer model (RTM) at an elevation angle of 41.8° for both 13.0 GHz (top panels) and at 31.6 GHz (bottom panels) channels as a function of surface rain rate. Stratiform and convective rainfall is plotted on the left and right panels, respectively.

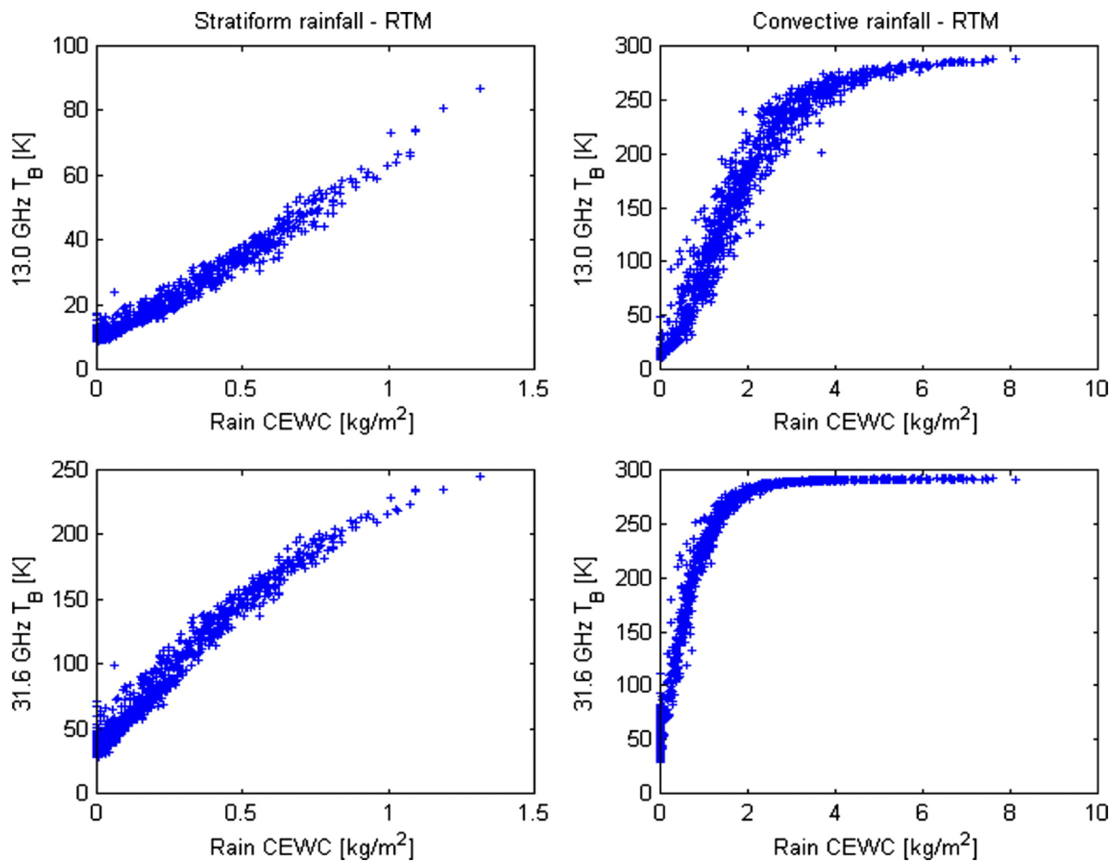

Figure 2 Same as in Fig. 1, but with respect to the columnar equivalent water content (CEWC) of cloud and rain hydrometeors.

with non-linear inverse problems (e.g., Vivekanandan and Li, 1997; Del Frate and Schiavon, 1999). Moreover, NN algorithms can be considered fairly efficient techniques once the training stage has been accomplished. As a benchmark, the results of the proposed neural-network technique is compared with a previously-developed regression algorithm, which is briefly summarized in the following.

For the aim of estimating columnar water and ice contents, as well as optical extinctions, the so-called Bayesian approach (originally applied to spaceborne measurements) to estimate rain and ice profiles might be applied, but is beyond the scopes of this work (e.g., Marzano et al., 1999; Tassa et al., 2003). From an inverse problem point of view, retrieving a content profile, instead of a vertically-integrated value, is just a matter of estimating more parameters with same number of measurements. The strong opacity of rainfall poses some strong limitations to the aim of profile estimation from ground observations.

Neural-network retrieval algorithm

The multi-layer perceptron architecture, here considered, denotes useful stochastic approximation properties. Most neural-network (NN) applications have only one or two hidden layers, since it is known that to approximate a function, characterized by an arbitrary degree of non-linearity, to a given accuracy, at most two hidden layers are needed (Hertz et al., 1991). In this work we proposed a physically-based NN approach to the passive microwave estimation of rain intensity and extinction. This means that we have used the modeled cloud-radiative data set, described in the previous section, to completely train the NN retrieval algorithm.

An interesting distinction between the non-linear modeling capability of NN models and that of polynomial expansions is that, with only a few parameters, the polynomial expansion is only capable of learning low-order data variability. In contrast, even a small NN is fully non-linear and is not limited to learning low-order data variability. A critical issue on NN modeling is that, due to the large number of parameters and great flexibility, the model output may fit the data very well durino the training stage, but may fail during the test stage. This behavior results from data overfitting, that is the NN fitted the training data so well that it fitted to the noise as well. NN overfitting may be overcome by carrying out a proper pruning of the NN (e.g., Del Frate and Schiavon, 1999). The generalization capability of a NN is basically related to the representativeness of the training data set (Vivekanandan and Li, 1997).

For this radiometric application, we have chosen a feed-forward neural network having, besides the input layer with N_i observables, a hidden layer of neurons with tan-sigmoid transfer functions and N_h neurons and an output layer of neurons with linear transfer functions and N_0 neurons. A schematic representation of the implemented NN is shown in Fig. 4. Instead of the standard back-propagation, for a faster training, we have used the Levenberg—Marquardt algorithm (Hagan and Menhaj, 1994).

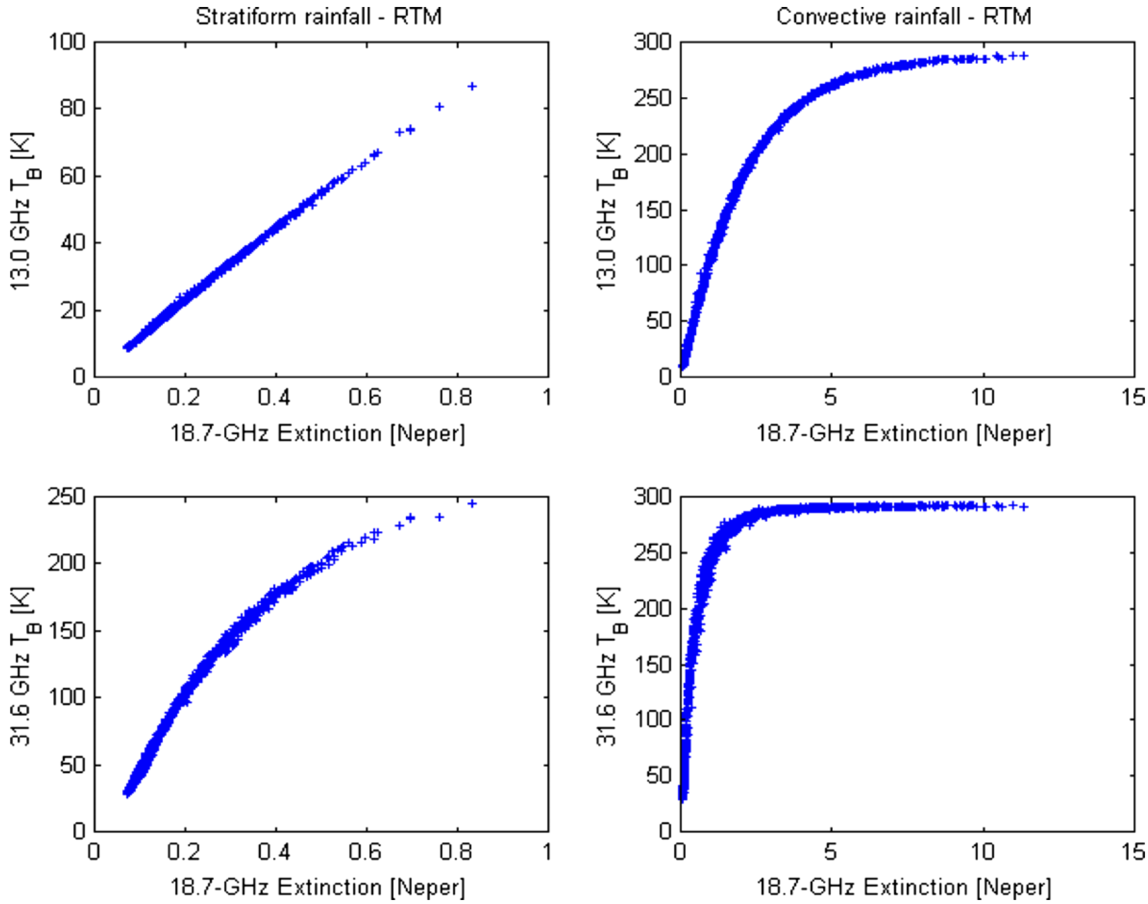

Figure 3 Same as in Fig. 1, but with respect to the slant-path total extinction (Neper) at 18.7 GHz.

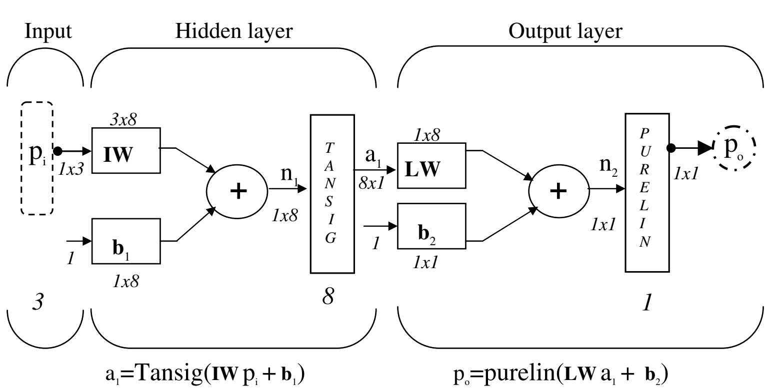

Figure 4 A schematic representation of the feed-forward Neural-Network used for retrieving rainfall intensity and extinction. The NN is characterized by an input, a hidden and an output layer with 3, 8 and 1 nodes, respectively. IW stands for input weights, LW for the layer weights, p_i for the measured inputs, *b* for the bias, *n* for the layer inputs, *a* the layer outputs, p_o are the network outputs, *Tansig* is the sigmoidal tangent activation function and *Purelin* is the output linear function. Note that numbers indicate either the variable dimension or the number of nodes, while bold indicate arrays.

A ''pruning'' procedure has been applied to select the optimum number of hidden neurons, yielding $N_h = 8$. In order to further speed up the algorithm efficiency, the NN has been run to provide one output parameter at time, that is with $N_0 = 1$. For improving the generalization capabilities of the network, the training process was performed monitoring the error between the network outputs and the targets on a test data set, independent of the training one, and stopping the process when a minimum of such error was found.

Multiple-regression retrieval algorithm

For comparison, a previously-developed algorithm, based on a variance-constrained multiple-regression (VMR) technique, has been derived from the same cloud-radiative data set described above (Marzano et al., 2002; Crone et al., 1996). Briefly speaking, assuming a cubic relationship between the rain rate R and measured T_B, the estimator of rain rate (in mm/h) can be written as follows:

$$\widehat{R} = a_{00} + \sum_{k=1}^{N} [a_{1k} T_B(f_k) + a_{2k} T_B^2(f_k) + a_{3k} T_B^3(f_k)], \qquad (2)$$

where f stands for the available radiometric frequencies. Similar expressions can be written for the estimate of the columnar equivalent liquid water contents (CEWC) of each hydrometeor, that is for C_h with h = c, r, g, i for cloud, rain, graupel, and ice species, respectively (in kg/m^2) and the total extinction τ_f (in Neper) with f the considered microwave frequency.

It is worth mentioning that the regression coefficients are computed by applying the constrained-variance technique where the constrained factor is determined by using proper criterion. This choice is justified by considering that, when operating a radiometric sensor in rainfall, spurious effects (such as the water film on the radiometer antenna) can cause unexpected response variability which translates into input noise. This scenario requires a robust inversion technique and the variance-constrained method has proved to have such a characteristics.

Numerical tests

As a first test of the NN retrieval algorithm, we have used synthetic data, obtained from the simulated database, but independent of the data set exploited for algorithm training. The test has been performed on the retrieval of both rain rate R and on the total extinction τ at 18.7, 39.6 and 49.5 GHz using the whole stratiform and convective rain data set.

Table 1 shows the results for rain rate retrieval in terms of root mean square (RMS) errors for different configuration of radiometric frequency set. Values of neural-network sensitivity to diverse initial conditions (expressed as standard deviation of the RMS's) show that, even though neural networks are generally more accurate than cubic regressions, this performance can be affected by the dependence on initial set up of the neural-network.

Table 2 shows the comparison between the multiple regression and the neural-network with respect to microwave extinction, computed at beacon frequencies of 18.7, 39.6 and 49.5 GHz. The neural-network algorithm shows a significant improvement in terms of RMS with respect the cubic regression.

Table 1 Root mean square (RMS) errors (in mm/h) for rain rate retrieval tests on synthetic data

Frequency (GHz)	Regression	Neural network	
	RMS	RMS	Sensitivity
6.8	5.0	4.8	0.1
10.6	5.1	4.6	0.1
13.0	5.3	4.5	0.1
23.8, 36.5	5.7	4.9	0.5
13.0, 23.8, 31.6	4.8	4.4	0.2
23.8, 36.5, 50.2	5.5	4.6	0.2
23.8, 31.6, 53.0	5.1	4.5	0.3
6.8, 23.8, 36.5	4.6	4.4	0.1

Values of the neural-network sensitivity (i.e., standard deviation in mm/h).

It is interesting to note that for both retrieval algorithms the set of 6.8, 23.8, and 31.6 GHz channels is the best choice followed by the set of 13.0, 23.8, and 31.6 GHz channels. This result is consistent with what obtained by Marzano et al. (2002), using only the variance-constrained regression algorithm and further emphasizes the predominant role of lower frequencies for rain monitoring by ground-based passive microwave techniques. A practical choice should be a compromise, however, between T_B frequency sensitivity and antenna beamwidth, being the latter affected by larger antenna size at lower frequencies.

Previous computations have been also repeated in order to evaluate the impact of using a larger number of input data. A cloud-radiative data set, made of 5000 composite profiles, has been tested. Numerical results show that the a data set larger than 5000 points does not produce significant changes in terms of retrieval accuracy for our application.

Application of neural-network retrieval algorithm: case study

The neural-network retrieval technique has been tested by resorting to available data of a case study, already used for testing the multiple regression algorithms (Marzano et al., 2002). Rainfall and slant-path extinction data, acquired at the ITALSAT-satellite ground-station located in Pomezia (Rome, Italy) and managed by Fondazione Ugo Bordoni (FUB), have been used. Since April 1994 measurements of the three ITALSAT propagation beacons at 18.7, 39.6, and 49.5 GHz at 41.8° elevation angle have been performed every second at an elevation angle of 41.8° with a receiver-antenna of 3.5 m.

Concurrent and co-located measurements performed by two microwave radiometers, pointed to the ITALSAT satellite at 41.8° elevation angle, and a set of ground meteorological instruments also including a tipping bucket rain gage, have been synchronously logged every 4 s by the ITALSAT ground-station. The radiometric data at 13, 23.8 and 31.65 GHz have been basically used to assess the clear-air atmospheric reference level for calibrating the ITALSAT beacon clear-air path attenuation. A more detailed description of the instrumentation and the calibration procedure is given by Marzano et al. (2002) and Han and Westwater (2000).

We stress the fact that the validation of microwave radiometric retrieval is fairly cumbersome task. Indeed, the opportunity to access to satellite beacon data is very unique since it allows us to compare path integrated measurements and products in a homogeneous way. This contrasts with the comparison of rain rate radiometric estimate with rain gauge data, which are point and time-integrated measurements at ground not necessarily representative of the atmospheric opacity structure above.

In order to show an example, we have selected a case of light-to-moderate rainfall, observed in Pomezia on May 3, 1998. A moving average with 1-min window and 1-min

Table 2 As in Table 1, but for path extinction retrieval (in Neper) at 18.7, 39.6 and 49.5 GHz

Frequency (GHz)	18.7 GHz			39.6 GHz			49.5 GHz		
	Regression	BP neural network		Regression	BP neural network		Regression	BP neural network	
	RMS	RMS	Sensitivity	RMS	RMS	Sensitivity	RMS	RMS	Sensitivity
6.8	0.0795	0.0776	0.0003	0.3716	0.3498	0.0056	0.5025	0.4501	0.0039
10.6	0.1299	0.0523	0.0035	0.3554	0.2768	0.0038	0.4335	0.3799	0.0034
13.0	0.2129	0.0656	0.0062	0.5060	0.2770	0.0034	0.5794	0.3912	0.0104
23.8, 36.5	0.4805	0.2908	0.0637	1.1057	0.6539	0.0032	1.2364	0.6839	0.1716
13.0, 23.8, 31.6	0.1807	0.0730	0.0099	0.4415	0.2662	0.0142	0.5153	0.3442	0.0273
23.8, 36.5, 50.2	0.4498	0.2392	0.0636	1.0379	0.6624	0.2541	1.1653	0.6555	0.0965
23.8, 31.6, 53.0	0.4436	0.2429	0.0388	1.0287	0.5699	0.0749	1.1583	0.7232	0.2019
6.8, 23.8, 36.5	0.0471	0.0454	0.0005	0.2342	0.2300	0.0010	0.3251	0.3226	0.0017

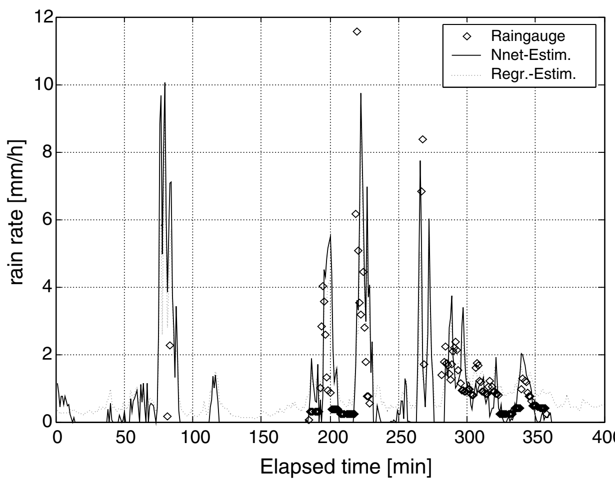

Figure 5 Comparison between surface rain rate (mm/h), measured by a rain gauge at Pomezia (Rome, Italy) ground-station on May 3, 1998, with that retrieved by the multi-frequency microwave radiometer using both multiple regression and neural-network algorithms.

sampling period has been applied to decimate raw data stream. Fig. 5 shows the comparison between the surface rain rate, measured by the rain gauge, with that retrieved by the multi-frequency microwave radiometer using the neural network algorithm and, for comparison, the multiple-regression technique. Fig. 6 shows the estimate of columnar equivalent rain water content derived from microwave radiometric using both neural network and multiple-regression algorithms. In the latter case, there is not any reference data to be compared with, but is interesting to note that the rain water contents around the peaks are above 0.5 kg/m^2, values which are typical of low-to-moderate rain regimes. Moreover, Fig. 6 shows a consistency between the NN and regression retrieval results.

Besides a fairly good consistency between both retrievals and measurements, Fig. 5 points out the capability of the NN algorithm to retrieve zero R values, in accordance with the rain gauge. On the contrary, the regression-based retrievals tend to be affected by a bias, even though for values less than 1 mm/h.

As a further example, in Fig. 7 the comparison between slant-path total extinction, measured by the microwave beacon at 18.7 GHz, with that retrieved by applying both

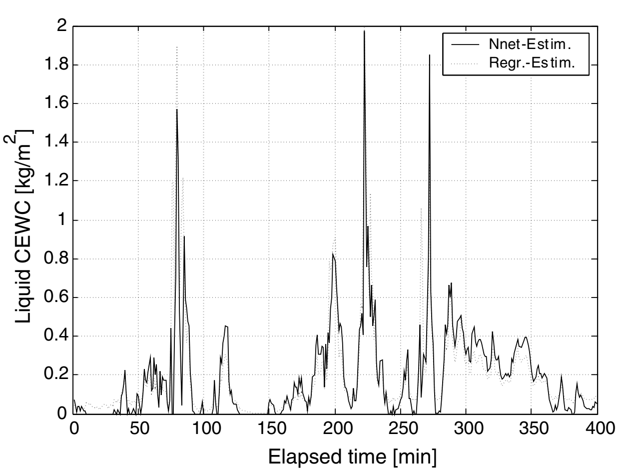

Figure 6 Estimate of columnar equivalent liquid water content (CEWC), derived from microwave radiometric data acquired at Pomezia (Rome, Italy) ground-station on May 3, 1998, using both multiple regression and neural-network algorithms.

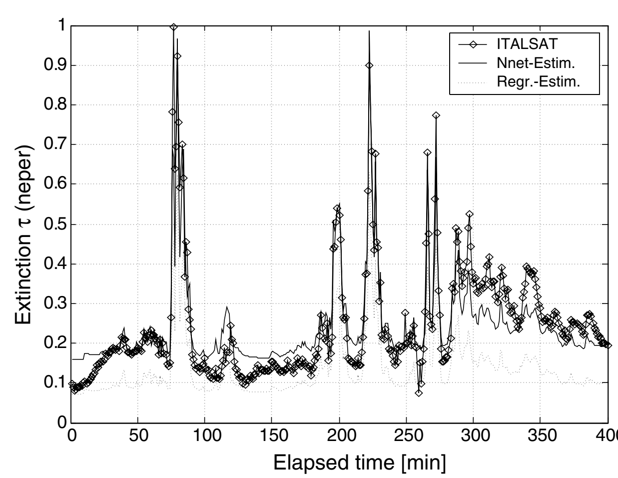

Figure 7 Comparison between slant-path total extinction (Neper), measured by the microwave beacon at 18.7 GHz, with that retrieved by applying both multiple regression and neural-network to microwave radiometric data.

multiple regression and neural-network to microwave radiometric data is shown. Figs. 8 and 9 show the same as in Fig. 6, but at 39.6 and 49.5 GHz, respectively. Again, especially at 18.7 GHz, the regression exhibits a bias, which yields a general underestimation of the total extinction.

To give a quantitative picture of this experimental analysis, estimation error of NN and VMR can be compared. The root mean square (RMS) error between VMR-based estimated and measured rain rate is about 1.4 mm/h, while when considering the NN retrieval, the RMS error is about 1 mm/h. The bias and root mean square (RMS) difference for path extinction for multiple regression are −0.1 Neper (Np) and 0.07 Np at 18.7 GHz, − 0.18 Np and 0.19 at 39.6 GHz, −0.14 Np and 0.29 at 49.5 GHz, respectively. Corresponding results for neural-network are 0.002 Np and 0.06 Np at 18.7 GHz, −0.007 Np and 0.17 Np at 39.6 GHz, −0.02 Np and 0.23 Np at 49.5 GHz, respectively. Neural-network algorithm confirms a better performance both in terms of error bias and RMS. Previous results have been also confirmed by the analysis of several stratiform and convective rainfall case studies during the 1998 year.

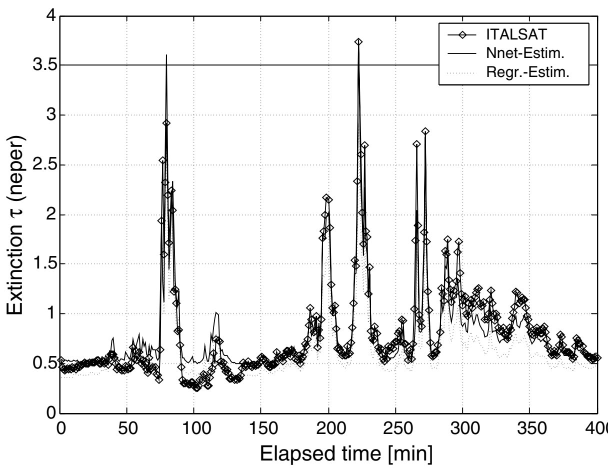

Figure 8 Same as in Fig. 6, but at 39.6 GHz.

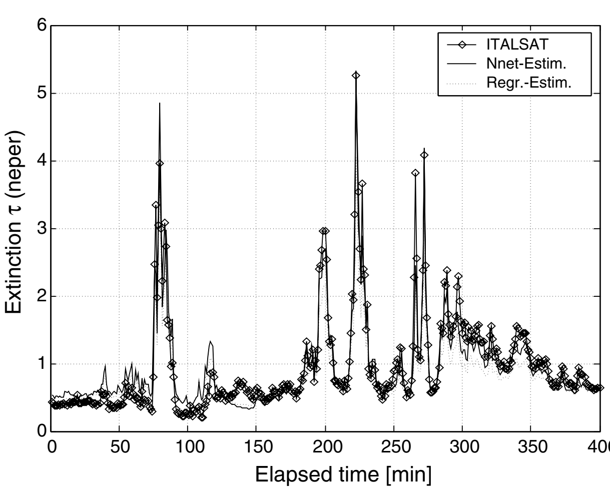

Figure 9 Same as in Fig. 6, but at 49.5 GHz.

Conclusions

A new neural-network based inversion algorithm for ground-based retrieval of surface rain rate and integrated cloud parameters has been proposed and tested. The retrieval algorithm has been trained by numerical simulations of a radiative transfer model applied to microphysically-consistent precipitating cloud structures. The neural network technique has been tested on synthetic data in order to understand their potential for estimating rain rate, columnar hydrometeor contents, total extinction and to select the best frequency set. A comparison with a previously-developed multiple-regression algorithm rain extinction measurements, derived from ITALSAT-satellite channels, have been performed for a selected case of light-to-moderate rainfall, characterized by a significant dynamic range. A fairly good agreement between NN-based estimates and measurements has been achieved. As compared to the regression approach, the NN retrieval algorithm tends to provide a better accuracy and a reduced error bias, especially for low-to-moderate rain rates. These results, proved by other case studies carried out on data available during 1998, denote encouraging perspectives for the proposed passive microwave technique.

Future work should be devoted to the analysis of a larger set of case studies in different climatological areas in order to assess the applicability of the entire retrieval procedure. As mentioned, a preliminary validation in terms of path attenuation is foreseen due to the peculiar remote sensing problem. Some perspectives and improvements of the proposed passive microwave can be envisaged. The angular scanning capability of a ground-based radiometer, typically used for calibration purposes, could be very useful to verify the horizontal homogeneity of the raining atmosphere. Note that the latter hypothesis is behind the radiative transfer model applied to vertically-stratified atmosphere. This problem may be removed by resorting to the local homogeneity within the beamwidth and by carrying out a modified radiative transfer computation along the inclined path (Marzano et al., 1999b). Moreover, by utilizing the scanning information, there might be the opportunity to develop new algorithms to retrieve the gross vertical profiles of hydrometeors. Finally, the integration of ground-based rain sensors, such rain gauges, microwave radiometers, weather radars and cloud ceilometers, should prompt the development of synergetic algorithms for accurate troposphere monitoring of rainfall fields.

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