Design of a rain rate retrieval algorithm using artificial neural network and the advanced technology microwave sounder

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Abstract.-

Passive microwave remote sensing techniques have shown to be a useful tool in order to retrieve atmospheric parameters on basis of radiative transfer fundamentals. However, due to the difficulties related with both numerical and computing complexity to model the physical phenomenology involved in atmospheric dynamics, some different techniques, such as Artificial Neural Networks (ANN), have been tested to find the mathematical relationship between atmospheric state variables and measurements carried out at a given time by satellite instruments. In this paper, it is presented a heavy rain-rate retrieval algorithm (ANN183) developed by using both an artificial neural network trained through the L-BFGS algorithm and measurements related with the strong water vapor absorption line at 183 GHz provided by the Advanced Technology Microwave Sensor (ATMS) aboard of the National Polar-orbiting Partnership (Suomi-NPP) platform of the National Oceanic and Atmospheric Administration (NOAA-USA). Preliminaries results showed a strong potential to reproduce the spatial distribution of rainfall when is compared with estimates provided by gauges measurements.

Keywords: atmospheric remote sensing; rain rate retrieval algorithms; artificial neural networks; ATMS

Diseño de un algoritmo para estimación de tasa de precipitación usando redes neuronales artificiales y la sonda de microondas de tecnología avanzada

Resumen.-

Las técnicas de teledetección usando microondas pasivas, han mostrado ser una herramienta útil para estimar parámetros atmosféricos a partir de fundamentos de transferencia radiativa. Sin embargo, debido a las dificultades computacionales asociadas con complejidades de orden numérico para modelar los fenómenos físicos que tienen lugar en la dimámica atmosférica, se han probado diversas técnicas, tales como redes neuronales artificiales, para definir relaciones matemáticas funcionales entre el estado de las variables atmosféricas y las mediciones realizadas por intrumentos a bordo de plataformas satelitales. En este trabajo, se presenta un algoritmo (ANN183) para estimar tasa de precipitación desarrollado a partir del entrenamiento de redes neuronales mediante el método L-BFGS, y usando mediciones relacionadas con la fuerte línea de absorción por parte del vapor de agua a 183 GHz proporcionadas por la Sonda de Microondas de Tecnología Avanzada (ATMS, por sus siglas en inglés) a bordo de la plataforma de la alianza nacional de satélites polares Suomi-NPP de la Administración Nacional del Océano y la Atmósfera (NOAA). Los resultados preliminares muestran un potencial relevante para reproducir la distribución espacial de precipitaciones, lo cual fue evidenciado mediante comparaciones realizadas con datos proporcionados por estaciones pluviométricas en superficie.

Palabras clave: teledetección atmosférica; estimación de tasa de precipitación; redes neuronales artificiales; ATMS

Recibido: mayo 2016
Aceptado: julio 2016

1. Introducción

The brightness temperature (BT) at a given atmospheric region might be linked to the electromagnetic density power measured by a radiometer through the radiative transfer equation [1, 2]. However, instead of that, commonly the microwave satellite rain-rate retrieval algorithms are developed by defining a mathematical or a statistical dependence [3, 4]. Some well known techniques to build this relationship are regression models [5], statistical approaches [4, 6], radiative approaches [7], physical-statistical [8], numerical cloud models [9], artificial neural networks [10]. In this work, this relationship is modeled through an artificial neural network approach. In addition, the improvement of capabilities to develop rain rate retrieval algorithms, using both artificial neural networks and data from the Advanced Technology Microwave Sounder (ATMS), is discussed in this work.

Some researchers have reported feasibility and accuracy to estimate rainfall rate from passive microwave satellites data by using artificial neural networks [10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]. Nevertheless, with the launch of the Advanced Microwave Sounding Units (AMSU) sensors, the spectral information in microwave spectrum about the atmosphere was greatly increased. For instance, the inclusion of channels centered at 183 GHz in AMSU has provided invaluable information on the water vapor content, hydro-meteors concentration, drop liquid water, vertical atmospheric profile parameters, etc.

Some lessons learned since using AMSU data to train ANNs to retrieve rain rate are: i) The development of rain rate retrieval algorithms based on artificial neural network are suitable when are combined channels centered at 54 and 183 GHz [18], ii) the 183±7GHz channel shows high sensitivity to rainfall due to its low sensitivity to surface emission, however in cold and dry regions, where increase the signal distortion for the surface emission contribution, the use of a more opaque channel such as 183±5 GHz or 183±1 GHz trends to improve the rainfall estimates accuracy [19], iii) the atmospheric energy budget is affected by surface emissions, for this reason, to reach an optimum accuracy level, it is convenient to develop algorithms for rain rate retrieval over land and over ocean separately [20], iv) rain rate estimates over land is less precise than over ocean in the case of light rainfalls. In contrast, in heavy rainfall events, the rain rate is underestimate because of the extinction of radiation caused by the ice cloud particles of the convective clouds. This interaction decreases the spaceborne radiometer sensitivity for detecting cloud liquid water content. [21].

Radiometric and channels features of ATMS are mostly similar to AMSU, however, the inclusion of a set of variations represents an important increase in capabilities because of the possibility to make observations for 3 additional frequencies values [23]. In order to retrieve rain rate in heavy precipitation events, using the Advanced Microwave Technology Sensor (ATMS), a methodology to design an algorithm able to estimate rainfall intensities using brightness temperature as data input is presented in this work. While In this context, this work deals with two issues, first, with the analysis of properties of ATMS, in order to retrieve rain rate by training a set of artificial neural networks, and second the presentation of a methodology to design an artificial neural network to retrieve rain rate using ATMS data.

2. The ANN183 Algorithm

2.1. The Concept

In *ANN183*, ANN stands for artificial neural network and 183 for the ATMS channels centered in the strong absorption line of water vapor at 183 GHz. The development of the ANN183 algorithm involved two stages, the design and training of the ANN, and the design of the retrieval algorithm. The data used to train the neural network was conformed by simulated brightness temperature of the ATMS channels and the respectives rain

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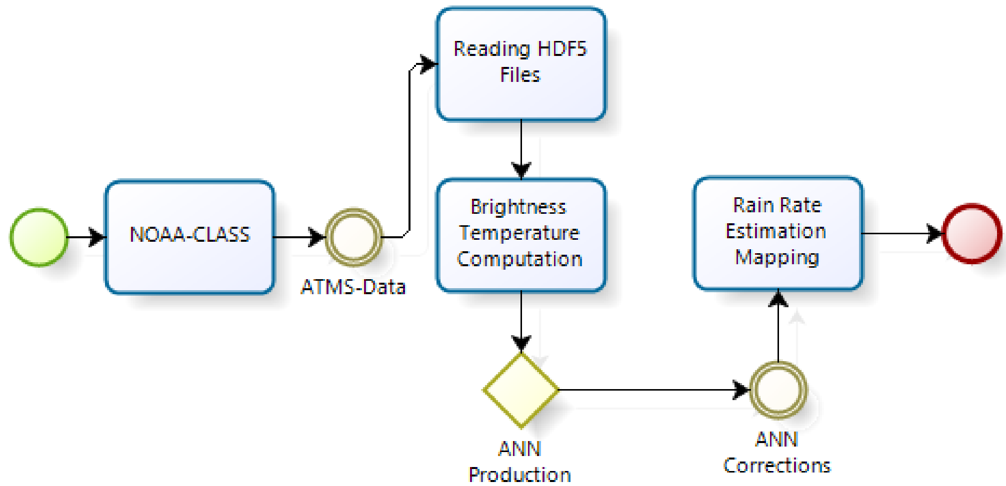

Figure 1: Flowchart of the ANN183 Algorithm

rate values for that spectral information, for both summer and winter periods. The data simulation was carried out by using the radiative transfer model for the TIROS Operational Vertical Sounder (RTTOV v-10) [24].

The algorithm is composed by 5 modules, which can be observed in the Figure 1. The first module is the ATMS data down-loader procedure, which is accomplished through the on-line NOAA-CLASS data manager . NOAA-CLASS facilitates the choice of data to be downloaded, by taking as parameters the date and the geographical location for the acquisition, also it is possible to visualize the available ATMS scenes before download it. Once the ATMS data have been downloaded, the second modules is used to read and setting up the data to be used as brightness temperature input into the algorithm. At this point, it is important to highlight that ATMS data is provided in HDF5 file format, and the reading and extraction of data from HDF5 format was performed by using the open source HDF5 library for C++. In this step, latitude (lat) and longitude (lon) are read for each pixel in the scene, and also the antenna temperature which is expressed as a digital quantity that must be converted to brightness temperature magnitude. The third module does the computation of brightness temperature from the ATMS data using the equation (1).

$$T_b = \left(\frac{330}{2^{16}-9}\right) * DN, \tag{1}$$

where T_b is the brightness temperature, and DN is the digital number of the antenna temperature variable for each ATMS channel. The HDF5 data format is a 3D cube in which the spatial plane have dimension of 180x96 pixel, and the z-axis has 22 layers, one for each ATMS channel. In this context, when applying equation (1) to ATMS data, it is possible to built a file conformed by 22 columns, one for each ATMS frequency channel, and each row in this data represents the brightness temperature for each pixel in the scene, and for each frequency. The fourth module consists in the execution of the artificial neural network. Once the fourth module is executed, a correction of the rain rate (RR) output is done. Finally, the fifth and last module is a map generation tool.

2.2. The Selection Criteria of ATMS Channels

The aim behind the training of artificial neural networks is to find optimal values for the bias and synaptic weights to minimize the error function between the network output and the expected output (objective) [25]. Since the characteristics of the network output is highly dependent of its design, in order to reach convergence and accuracy in the network output, the channels selected as input into the network, must be able to predict the output variable (rain rate). In other words, each channel assigned to every neuron in the input layer plays an important role in the generalization capability of the network, so a prior analysis about the physical relationship of each ATMS channel with the rain rate process must be carried out.

Table 1: Central frecuency operational value for the 22 ATMS channels, and espatial resolution features [23]

Channel	*Frecuency (GHz)*	*Nadir Resolution (km)*
1	23,80	75
2	31,40	75
3	50,30	33
4	51,76	33
5	52,80	33
6	53,59	33
7	54,40	33
8	54,94	33
9	55,50	33
10	f_{LO} = 57,29	33
11	f_{LO}±0,217	33
12	f_{LO}±0,322±0,048	33
13	f_{LO}±0,322±0,022	33
14	f_{LO}±0,322±0,010	33
15	f_{LO}±0,322±0,045	33
16	89	33
17	166,31	15
18	183,31±7	15
19	183,31±4,5	15
20	183,31±3,0	15
21	183,31±1,8	15
22	183,31±1,0	15

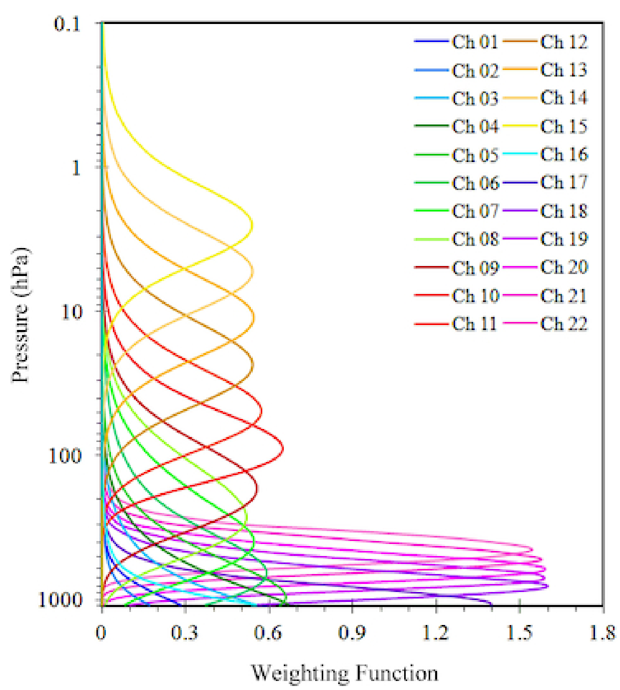

Figure 2: ATMS weighting functions [26]

In Table 1, are shown the central frecuencies values at which operate each ATMS channel. The weighting function for each ATMS channel is shown in Figure 2. In order to choose the optimal set of channels to be used as data input into the algorithm, it is important to consider the sensitivity of each channel to distinguish radiative parameters related to rainfall activities. Weighting functions shown that channels 9 to 15 are not enough sensitive to tropospheric composition, consequently they are underestimated for rainfall estimation.

Channels 1 and 2 have been neglected too, because they provide sparse information about water vapor and low clouds, as a consequence of the high sensitivity to radiative surface emissions. Channels 6, 7 and 8 have been also discarded, even when they are sensitive to tropospheric brightness temperature, a bias correction process should be carry out to remove the dependence on the scanning angle.

Therefore, the set of channels to be integrated into the ANN183 algorithm is composed by the channels 3, 4, 5, 16, 17, 18, 19, 20, 21 and 22. The aim of this work is to design an algorithm able to estimate rain rate in severe rainfall events over land surface. To do this, some experiments for different combinations of these channels were achieved [27], and the best results were found when all the listed channels are combined simultaneously (see Figure 2).

2.3. Design and Training of the ANN

The main module of the ANN183 algorithm is the artificial neural network, which must to be trained to generate a rain rate output with both satisfactory accuracy and reliability criteria. This task can be performed by selecting an appropriate artificial neural network training algorithm, also an optimum training strategy, providing a training data set that satisfies the dynamic characteristics of the phenomenon of precipitation as a function of the radiative properties that define the brightness temperature in the atmosphere. It is remarkable also the ANN architecture chosen for the algorithm.

In this context, considering the results reported by Bellerby [14], about the topology features required to emulate the non-linearity of the processes involved in the atmospheric phenomenon to describe precipitation and its mathematical relationship with radiative transfer variables measured by satellite sensors, the topology to be used in the ANN training process are neural networks with two hidden layer, the first one having 10 neurons and the second one having 5 neurons. The number of neurons in the input layer will be the same as the number of input variables into the algorithm, while the output layer will be represented by the rain rate estimation. The data provided into the input layer is scaled in order to guarantee numerical stability. The activation function used in the first and second hidden layer is the hyperbolic tangent, while the linear activation function was implemented in the output layer.

The relationship between the rain rate and the brightness temperature was found through a linear regression built considering the input and output layer of the network. For the sake of getting a satisfactory accuracy in the linear fitting, a training strategy has been implemented, and the performance of both L-BFGS and Quasi-Newton (QN) training methods were evaluated. The criteria to choice these algorithms are based on the assumption of the stability and the convergence cost related with algorithms of second orders like QN method, and taking account that L-BFGS is considered to be an evolutionary enhancement of the QN algorithm. Since this assessment, it is expects to find a sensitive approach in order to figure out about the performance countenance provided by recent advances in artificial neural network algorithms, and their applications to retrieve rain rate using atmospheric remote sensing principles [10].

2.4. The Mapping Module

An important task inside the ANN183 algorithm, is the rain rate map generation step. In this module are plotted both, the rain rate output of ANN183 for each ATMS scene, and the brightness temperature for each channel incorporated into the retrieval algorithm.

3. Results

The design of ANN183 derived relevant results in two aspects: the neural network training, and the rain rate output found by assess a heavy rainfall event.

3.1. The Neural Network Training

Table 2: Channels selection for the network training for rain rate retrieval over land pixels (L). These configurations are used for both, summer (LS) and winter condition (LW)

Id	*Experiment Code*	*Set of Channels*
1	LS_1/LW_1	3-4-5-16-17-18-19-20-21-22
2	LS_2/LW_2	18-19-20-21-22
3	LS_3/LW_2	5-17-18-19-20-21-22

The first decision to be taken, in order to configure the network topology, is the ATMS channel combination to be used as input. Following the criteria for channels selection discussed early, and results obtained in prior research [27], in Table 2 are shown the sets of channels considered for the network training.

Experiment 1 is integrated for all the channels considered to have both a physical relationship with precipitation radiative features and no need for the implementation of an exhaustive correction step prior to be used as input. Channels for experiment 2 have been selected due to this combination has reported good results for AMSU data implementations [5], while the experiment 3 was done in order to exploit specific features of ATMS [10, 28]. Each experiment was implemented in an ANN to be trained by both Quasi-Newton and L-BFGS algorithm, in order to looking for the best output. Results are shown in Table 4, where it can be observed that the best fitting is for the L-BFGS algorithm in the experiment 1. The implementation of the L-BFGS algorithm was possible by using the ALGLIB library, while QN was implemented through Open NN [29]. The third column in Table 4, denoted with a percent symbol is the percent difference in squared-R for both algorithms.

Since results reported in Table 4, we have selected the channels of the experiment 1 for the ANN design, and it was trained with the L-BFGS algorithm.

Table 3: Results summary for the correlation coefficients for networks trained using the L-BFGS and the Quasi-Newton (QN) algorithms [27]

Experiment	R^2 for *L-BFGS*	R^2 for *QN*	(%)
1	0.8391	0.6594	21.41
2	0.4510	0.3397	24.67
3	0.5854	0.3846	34.30

Table 4: Results summary for the correlation coefficients for networks trained using the L-BFGS and the Quasi-Newton (QN) algorithms [27]

3.2. Evaluation of a Heavy Rainfall Event

Aimed to evaluate from a qualitative point of view the output generated for the algorithm, a heavy rainfall event has been analyzed. On 30 April 2012, a severe rainfall took place over Kansas, Oklahoma, Missouri and Illinois, in United Stated of America, leading to some large areas affected by floods due to daily cumulated precipitation greater than 100 *mm*, according to the National Weather Service (NWS) report shown in Figure 3.a. Furthermore, in Figure 3.b it is shown the hourly precipitation map from 8:00 to 9:00 UTC, where they were identified three main precipitating nucleus: i) nucleus 1 was located between Oklahoma and Texas, with a maximum of 12.5 *mm*, ii) nucleus 2 located in the boundaries of Kansas (12.5 *mm*), Oklahoma (24.5 *mm*), Missouri (19.05 *mm*) and Illinois (19.05 *mm*), iii) nucleus 3 centered in Indiana with a maximum of 12.5 *mm*.

The output of ANN183 is shown in the Figure 3.c, where it is remarkable the similarity between the rainfall pattern reported by NWS and the output mapped by the ANN183. Main nucleus identified by the NWS have been also detected and produced with relevant accuracy. In relation with the rain-rate estimates values, it is important to mention that the data provided by the NWS is the hourly precipitation from 8:00 to 9:00 UTC, while the output generated by ANN183 is an instantaneous rain-rate. This data was acquired from measurements carried out at discrete time, for this reason, a quantitative analysis about the rain-rate estimation was dismissed in this work.

However, some key properties to be highlighted about the results are: 1) Accurate location of the precipitating cells, 2) clear discrimination between pixels with low and high precipitation intensity, 3) non-precipitating pixels classifieds as precipitating shows intensities lower than 3 *mm*.

4. Discussion and Conclusion

From a qualitative point of view, the implementation of ANN183 has shown feasibility to evaluate heavy precipitation events. The implementation of this algorithm is useful in heavy rainfalls because the noise could be separated from the precipitation signal. However, there is still a way to enhance the accuracy of the algorithm in light rainfall since the application of training data associated with strati-form clouds. This could have applications in the field of data assimilation for early warning models to floods or hazards related with severe rainfalls events. ANN183 was designed taking as reference the ATMS channels weighting functions in order to exploit the information collected by each channel in reference to the main radiometric features of precipitating clouds. The weighting functions showed that the radiometric characteristics of ATMS involve a set of channels that provide information about the vertical structures of clouds, which is an important contribution in order to estimate rain rate in convective systems.

In this context, the best fit was found when channels of high (near to 183 GHz) and low (near to 54 GHz) frequency were combined. Additionally, the choice of a training algorithm have a severe impact in the performance and generalization of the network. Particularly, the L-BFGS algorithm provided satisfactory accuracy levels. In comparison with AMSU, ATMS has more potential to estimate rain rate due to the inclusion of channels 19 and 21. The experiment 2 includes all the high frequency channels of AMSU, and they were not good enough to estimate the rain rate with a satisfactory accuracy level, while in the experiment 1, the quality of outputs is highly related with the inclusion of channels 19 and 21 from ATMS. The number of neurons in the input of the net is equal to the number of channels considered to be input into de algorithm, however the number of hidden layers was in all cases two,

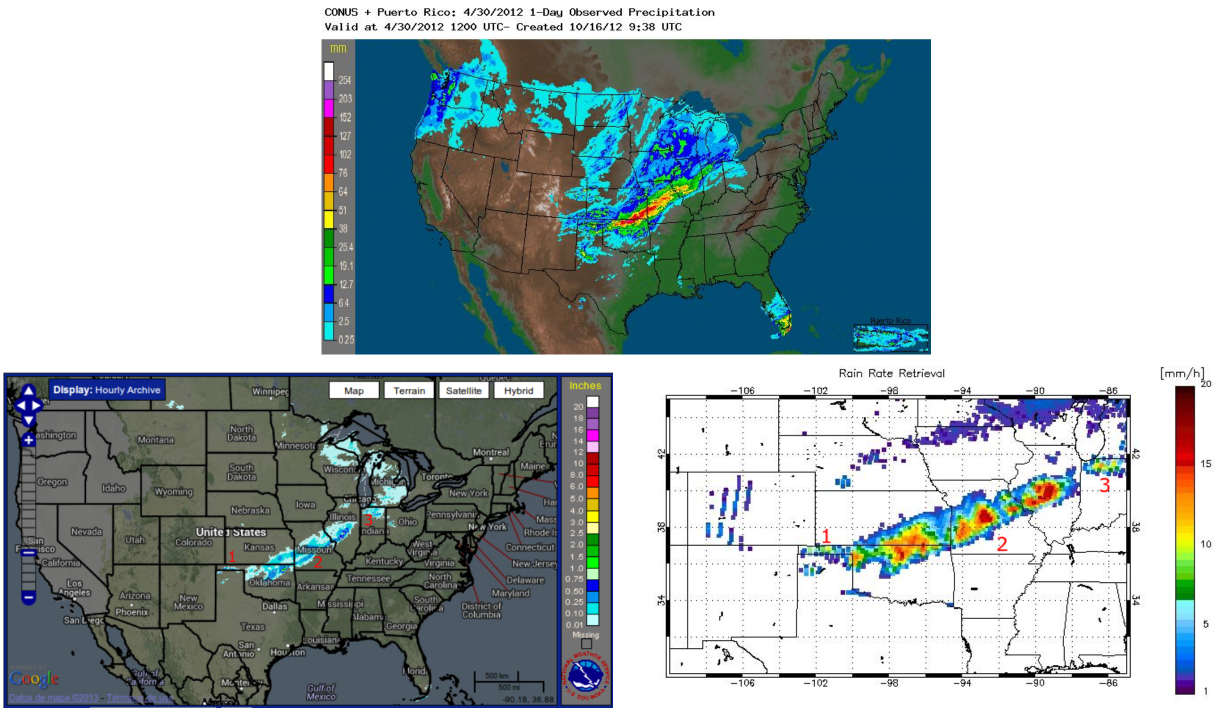

Figure 3: a) The Daily Precipitation map (up) shows the amount of precipitation that was accumulated within 24 hours [30], b) The hourly precipitation map (down-left) between 08:00 and 09:00 UTC, in which they can be observed three main precipitating nucleus labeled as 1, 2 and 3 respectively, and c) The instantaneous rain-rate map (down-right) generated by ANN183 using data captured from 8:00 to 8:08 UTC. Note that difference between the NWS hourly cumulated precipitation and the rain rate output of ANN183 are expected, and for this reason, a quantitative comparison between them would be ambiguous. The rain rate ANN183 output shows a noisy signal with an intensity less 5*mm*. Even when this noise could be filtered, this bias limits the accuracy of this algorithm to classify as precipitating pixels in a strati-form clouds cover.

with 10 neurons the first and 5 the second.

The instantaneous rain rate estimates done by ANN183 showed good performance to generate the precipitation intensities pattern reported by NWS. Also, the deeper convective cloud cells were associated with the highest rain rate in the scene. It is to be expected an underestimation of rainfall intensities related with convective clouds, however the implementation of a calibration step could decrease the difference in estimates. Further research are been developed in order to calibrate the output for intensities, and validation of the methodology.

Finally, the training data involved radiative conditios for summer and winter periods, so this algorithm have been developed for mid latitudes. In the case of lower latitudes, the training of an ANN using data more associated with the radiative properties of these environments could be necessary.

Agradecimientos

El autor agradece al Instituto de Altos Estudios Espaciales *Mario Gulich*, de la Comisión Nacional de Actividades Espaciales de Argentina por el soporte y financiamiento para llevar a cabo esta investigación. De igual forma, agradece la gentileza del Dr. Vincenzo Levizzani del CNR de Italia, y a su grupo de colaboradores, por el entrenamiento y transferencia de conocimientos en los tópicos discutidos en este trabajo.

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