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Rede Neural para a Previsão de Raios na Região Sudeste do Brasil

Neural Network for Lightning Forecasting in Southeastern Brazil

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Abstract

This paper introduces a lightning forecasting system using Neural Networks (NN) based on correlations between cloud-to-ground (CG) lightning flash data and meteorological variables obtained from MM5 (Fifth-Generation Penn State/NCAR Mesoscale Model) simulations in southeastern Brazil. Besides the area of nineteen high density lightning subregions selected from non-severe thunderstorms cases, the following model parameters were also used as inputs for the NN: divergence at 850 hPa and 200 hPa, temperature advection at 500 hPa, vertical velocity at 500 hPa, and water vapor-mixing ratio at the surface and 850 hPa. The target output of the neural system was the number of CG lightning flashes that would occur one hour in advance. Four cases, not previously trained, of high density lightning subregions were used to test the system efficiency. Although the testing cases were sufficiently different, a case with no occurrence of lightning has also been included in order to not introduce any bias on the analysis. The results of the lightning forecasting were promising, indicating that the NN technique associated with model variables from numerical simulations can be an efficient tool for predicting flash occurrence appropriately.

Keywords: *Lightning, forecasting, MM5 model, neural network.*

Resumo

Este artigo apresenta um sistema de previsão de raios para o sudeste do Brasil utilizando uma Rede Neural Artificial (RNA) baseada em correlações entre dados de relâmpagos nuvem-solo e variáveis meteorológicas de saída do modelo de mesoescala MM5. Foram utilizados como parâmetros de entrada da RNA a magnitude da área de 19 sub-regiões, de diferentes tempestades, com alta densidade de raios, e as seguintes variáveis do MM5: divergência em 850 hPa e 200 hPa, advecção de temperatura em 500 hPa, velocidade vertical em 500 hPa, e razão de mistura na superfície e em 850 hPa. A saída do sistema neural de previsão é o número de relâmpagos que possivelmente atingirá o solo na hora seguinte a dos campos atmosféricos simulados. Quatro sub-regiões com alta densidade de raios, não treinadas previamente, foram escolhidas para testar o sistema. Embora os casos de teste sejam suficientemente diferentes entre si, um caso sem ocorrência de relâmpagos também foi incluído para não tornar os testes tendenciosos. Os resultados foram promissores, indicando que a RNA associada a determinadas variáveis de simulação do MM5 pode ser uma ferramenta eficiente para a previsão da ocorrência de raios.

Palavras-chave: *Raio, previsão, modelo de mesoescala MM5, rede neural.*

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1 Introduction

Among many natural phenomena that contributed to the formation and evolution of the planet Earth, storms and lightning provoke particular interest of admirers and researchers because, although beautiful, they possess a destructive character. Lightning are electrical discharges in the atmosphere, followed by intense brightness, that occur due to the existence of an electric field that exceed the air dielectric capacity. Physical processes responsible for accumulating intense and different electrical charges within the cloud are not fully understood. In part this is due to the electrical structure of a thundercloud being quite complex, which depends on the result of microphysical and macrophysical processes that occur simultaneously within the clouds (Saunders, 1995; 2008). Brazil, due to its large territorial extension and to the fact of being the biggest tropical country in the world, presents intense electric activity. It is estimated that fifty million lightning flashes reach Brazil every year. This is equivalent to almost ten discharges per squared kilometer (Pinto Jr., 2009).

In this work, we introduced a lightning forecasting system using Neural Networks (NN) based on correlations between cloud-to-ground (CG) lightning flash data and meteorological variables obtained from MM5 (short for Fifth-Generation Penn State/NCAR Mesoscale Model) (Dudhia et. al, 2002) simulations in southeastern Brazil. So far, no study has associated lightning data, numerical simulation products and artificial intelligence techniques in an attempt to develop tools for predicting the occurrence of lightning. Frankel et al. (1991) constructed and trained neural net architectures to generate spatio-temporal maps of predicted probabilities of lightning over the Cape Canaveral Air Force Station and Kennedy Space Center. Input data for the network included the wind data, the electric field data, nearby lightning data, and the product Total Area Divergence developed by Watson et al. (1987). Given the preliminary nature of the study, the results were indicative of a promising direction. Nagae et al. (2000) proposed a fuzzy-neural network to predict the transient path of lightning location few hours ahead after its occurrence over Tokyo in the 1995 and 1997 summers. Comparing to the observational data, the results were reasonable as to the lightning locations, but needed to be improved regarding the flash density.

Figure 1 shows a sketch to illustrate the study's objective. The MM5 meteorological variables are preprocessed before becoming input in the NN, which returns the prediction of the number of CG flashes that would occur one hour later. In this case, the NN can be seen as a transfer function relating some input variables with an output, and considering a time delay between the input and output data. The real atmospheric dynamics responsible for connecting the chosen input variables with the output is sufficiently complex and, evidently, not well known. Our effort consists exactly in making the NN to learn this dynamics and foresee the atmosphere's behavior one hour later in the form of the number of lightning flashes that would reach the ground.

To impose the NN to have a forecasting character with real practical applicability, it seems reasonable to assume that it is necessary to satisfy specific conditions, such as: 1) The simulator is trustworthy or, at least, it confers numerical results with errors inside acceptable limits; 2) Although nonlinear, the nature (atmospheric dynamics) behaves approximately as an univocal function of some variables, meaning that different numerical values for a set of input variables induce different outputs (number of CG flashes) one hour later; 3) The phenomenon is time correlated, i.e., there is a correlation between the chosen input variables (meteorological variables one hour before) and the number of CG lightning flashes (one hour later); 4) The chosen input variables to the neural forecasting system are really representative of the phenomenon under analysis.

2 Lightning Data

Cloud-to-ground (CG) lightning flash data provided by the Brazilian lightning location system (RINDAT) (Pinto Jr., 2003) from October 2002 to March 2004 were used in this study. Figure 2 shows the map of detection efficiency for RINDAT for the year 2003. It is observed that in southeastern Brazil the detection efficiency of CG flashes is approximately 90%. In Figure 3, the color map (within DOM2) indicates the region of interest covering the Rio de Janeiro state, the southern portion of Espírito Santo state, the southeastern portion of Minas Gerais state, and the Atlantic Ocean. The sea extent in this area encloses important oil reserves in Brazil, which account for over 80% of the domestic production of oil and gas, and various platforms of ships and aircrafts, whose operation strongly depends on weather and oceanographic conditions. Therefore, it is strategic to identify reliably the occurrence of lightning in this region.

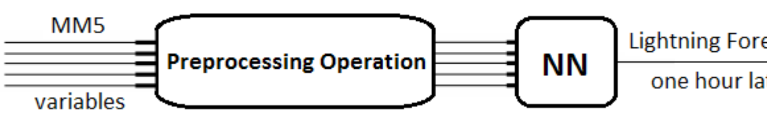

Figure 1. Basic diagram of the lightning forecasting system.

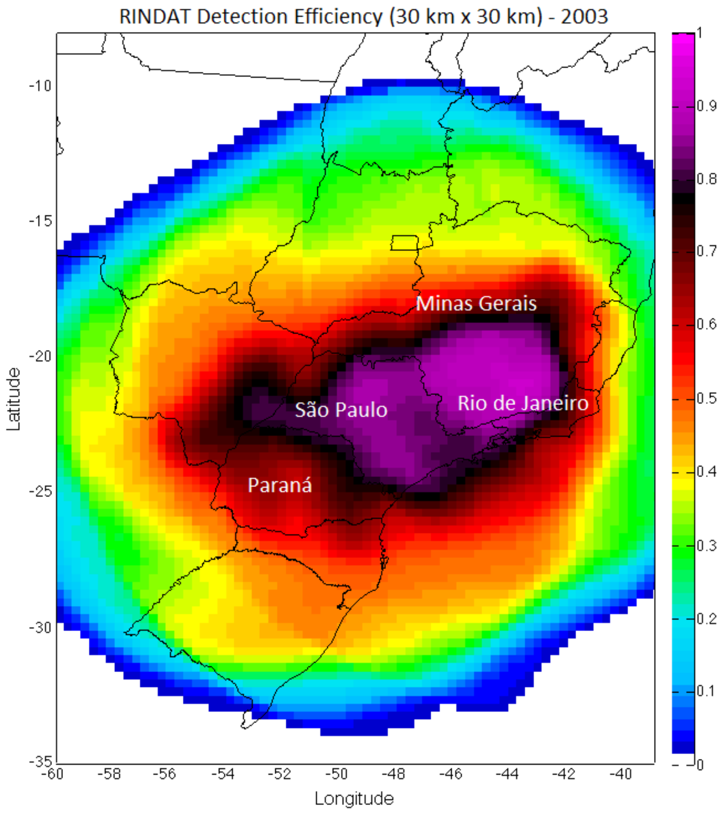

Figure 2. Map of the lightning detection efficiency of CG flashes for RINDAT for the year 2003 (Grupo de Eletricidade Atmosférica (ELAT)/ National Institute for Space Research (INPE)).

3 MM5 Mesoscale Model

The MM5 version 3 is a limited-area, nonhydrostatic, terrain-following sigma-coordinate model designed to simulate or predict mesoscale atmospheric circulation. The model is supported by several pre- and post-processing programs, which are referred to collectively as the MM5 modeling system (Dudhia et al., 2002). As illustrated in Figure 3, the model setup included a coarse 90 km grid (DOM1) (34° to 12° S and 60° to 30° W) and a nested 30 km domain (DOM2) (29° to 17° S and 47° to 33° W). In the vertical direction, 31 unevenly spaced full sigma levels were established.

The National Centers for Environmental Prediction/ National Center for Atmospheric Research (NCEP/NCAR) Reanalysis (hereinafter the NNR (Kalnay et al., 1996)), and 6-hourly resolution NNR global fields with 2.5° x 2.5° latitude-longitude horizontal grid resolution were used to initialize the model and nudge the boundaries of DOM1. The variables needed as boundary conditions for the MM5 model were temperature, wind, geopotential height and specific humidity at 17 pressure levels, surface pressure and sea surface temperature.

The model physics included the Kain-Fritsch 2 cumulus parameterization (Kain, 2004), the Schultz microphysics scheme (Schultz, 1995), the Medium-Range Forecast (MRF) boundary layer parameterization (Hong and Pan, 1996), the Rapid Radiative Transfer Model (RRTM) Longwave radiation scheme (Mlawer et al., 1997), and the Noah LSM model (Chen and Dudhia, 2001).

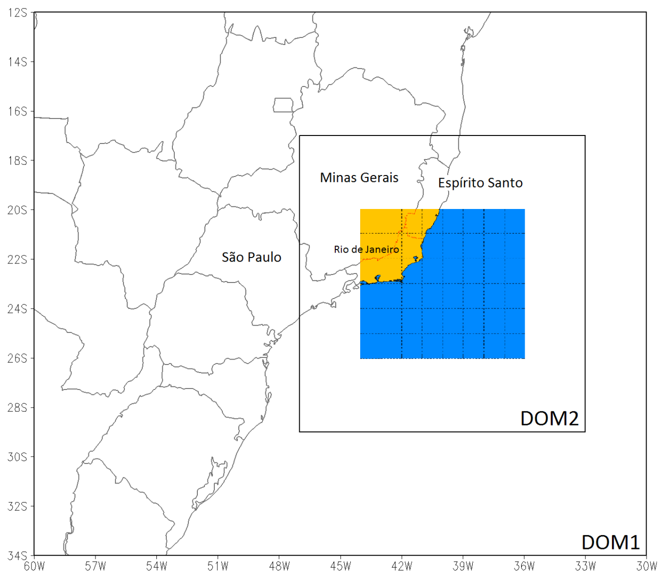

Figure 3. The MM5 domains: coarse domain (DOM1 – 90 km) and a nested domain (DOM2 – 30 km). The color map within DOM2 indicates the region of interest for the lightning forecasting.

4 NN Architecture

Artificial neural networks have been developed appearing to emulate the neural computing power of the human brain. Intellectual behavior such as pattern recognition, associative memory, and learning by example that is difficult to simulate with conventional means of artificial intelligence, is readily accessible to neural networks. As it is a subject worthy of great attention by the scientific community, there are several applications of artificial neural networks in different fields of science and technology (Ertugrul and Kaynak, 1997; Jung and Hsia, 1998; Gervini et al., 2003). Miller III et al. (1995) report an interesting description of the neural networks history.

The starting point for most neural networks is a model neuron, as in Figure 4. This neuron consists of multiple inputs and a single output. Each input is modified by a weight, which multiplies with the input value. The neuron combines these weighted inputs and, with reference to a threshold value and activation function, uses these to determine its output. Figure 5 illustrates how a backpropagation neural network with m layers of neurons is constructed. Multiple layers are arrayed one succeeding the other so that there is an input layer, multiple intermediate or hidden layers, and finally an output layer. Backpropagation neural networks are usually fully connected, which means that each neuron is connected to every output from the preceding layer or one input from the external world if the neuron is in the first layer, and, correspondingly, each neuron has its output connected to every neuron in the succeeding layer. The learning process in a neural network is called training. Training in a neural network requires a coach, someone that describes to the neural network what it should have produced as a response. From the difference between the desired response and the actual response, the error is determined and a portion of it is propagated backward through the network. At each neuron in the network, the error is used to adjust the weights and threshold values of the neuron, so that the next time the error in the network response will be less for the same inputs.

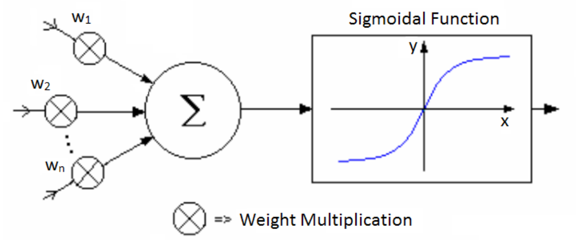

Figure 4. A model neuron. The weights parameters are represented by w1, w2 … wn. It was used a hyperbolic tangent (tanh) as activation function.

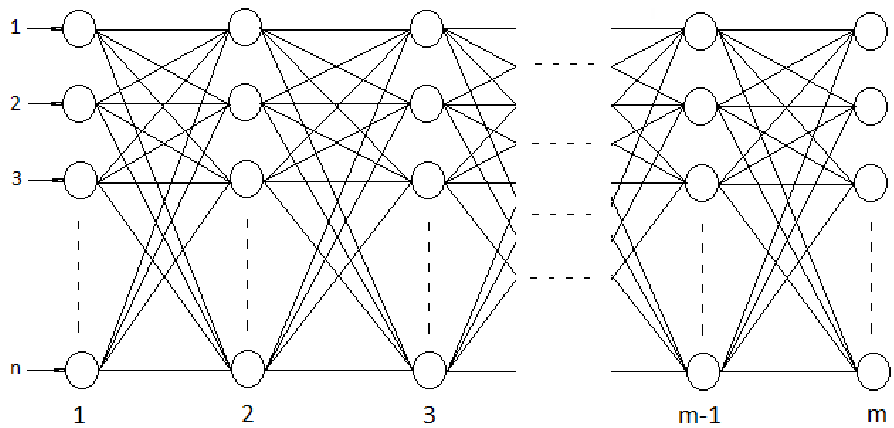

Figure 5. A generic backpropagation neural network with m layers of neurons.

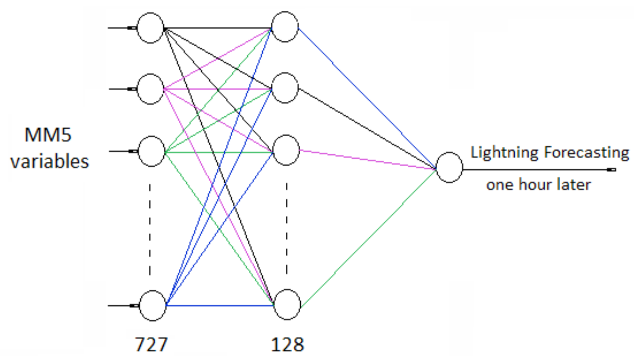

Figure 6. Neural network architecture of the lightning forecasting system.

The neural network architecture proposed to the lightning forecasting system is a backpropagation, multilayer, feedforward and fully connected network. It was used a backpropagation with momentum as training rule (Beale and Jackson, 1990; Fausett, 1994). As shown in Figure 6, the input layer is composed by 727 neurons containing the MM5 model variables chosen as potential predictors of lightning, and the area, in km^2, of high density lightning subregions. The preprocessing procedure applied to these parameters in order to convert them in the NN inputs will be presented in the subsection 4.1. A single intermediate layer with 128 neurons was used to learn the NN patterns. Fewer neurons (8, 16, 32, and 64) were also tested, but the best results were obtained with 128 neurons. The output layer has only one neuron, which represents the amount of CG lightning flashes that will occur during the next hour.

4.1 NN Input Variables

Twelve days of isolated and/or multicellular, non-severe thunderstorms were selected based on the lightning activity from March 2002 to February 2004. By analyzing the spatial distribution of the lightning flashes over the hours for each thunderstorm, it was possible to identify well configured high density lightning subregions. Figure 7 presents three examples of these areas, enclosed by black rectangles, for a thunderstorm occurred on November 19 and 20, 2003.

The following MM5 model variables were chosen as potential predictors of lightning: divergence (10^{-4} s^{-1}) at 850 hPa and 200 hPa, temperature advection (K/h) at 500 hPa, vertical velocity (m/s) at 500 hPa, and water vapor-mixing ratio (10^{-3} g/kg) at surface and 850 hPa. Every MM5 output from DOM2 was a 150x150 matrix, which was cropped according to the geographic coordinates of the lightning subregions, and immediately interpolated in two dimensions using Taylor series truncated at the first order to an 11x11 matrix. This interpolation was necessary to guarantee a fixed number of neurons in the NN input layer (121 neurons for each MM5 variable). To illustrate this procedure, Figure 8 shows how the divergence at 200 hPa was preprocessed for the first case of Figure 7.

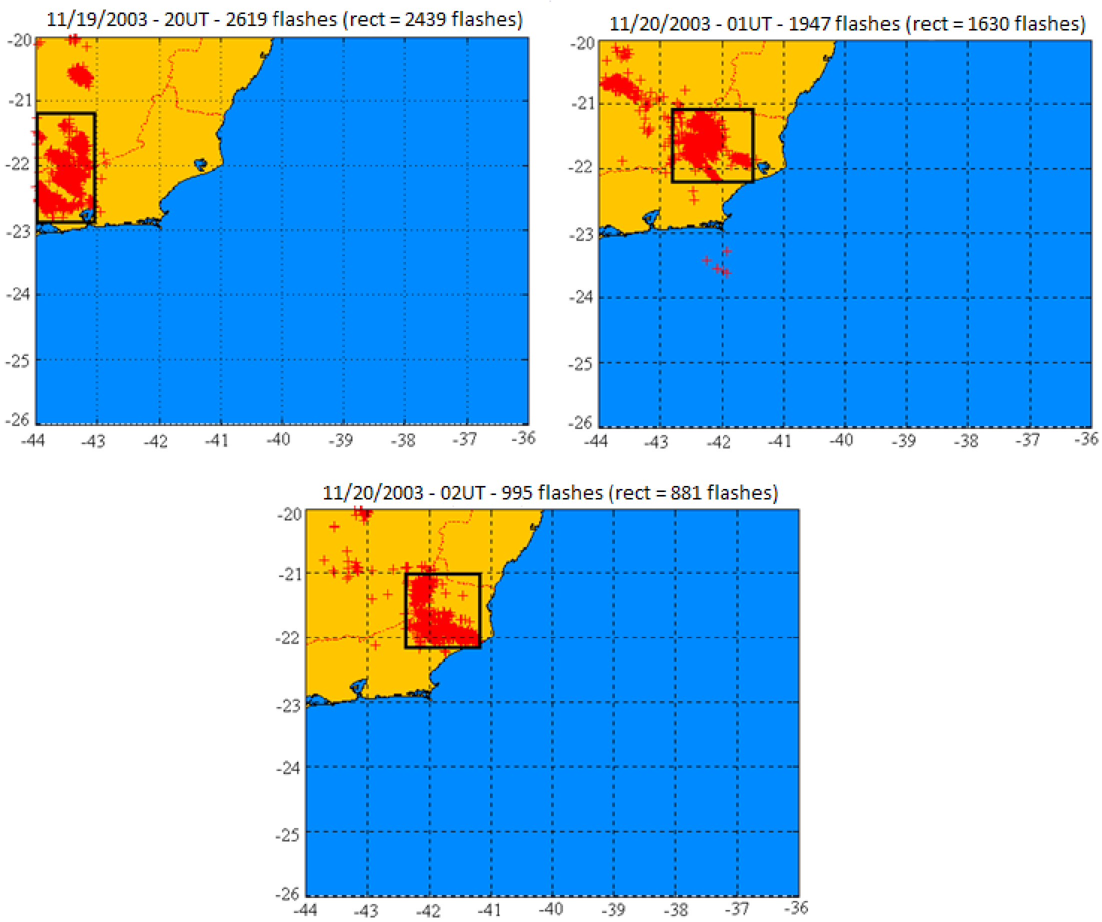

Figure 7. Examples of high density lightning subregions (black rectangles) for the thunderstorm occurred on November 19 and 20, 2003. The red crosses represent the CG lightning flashes.

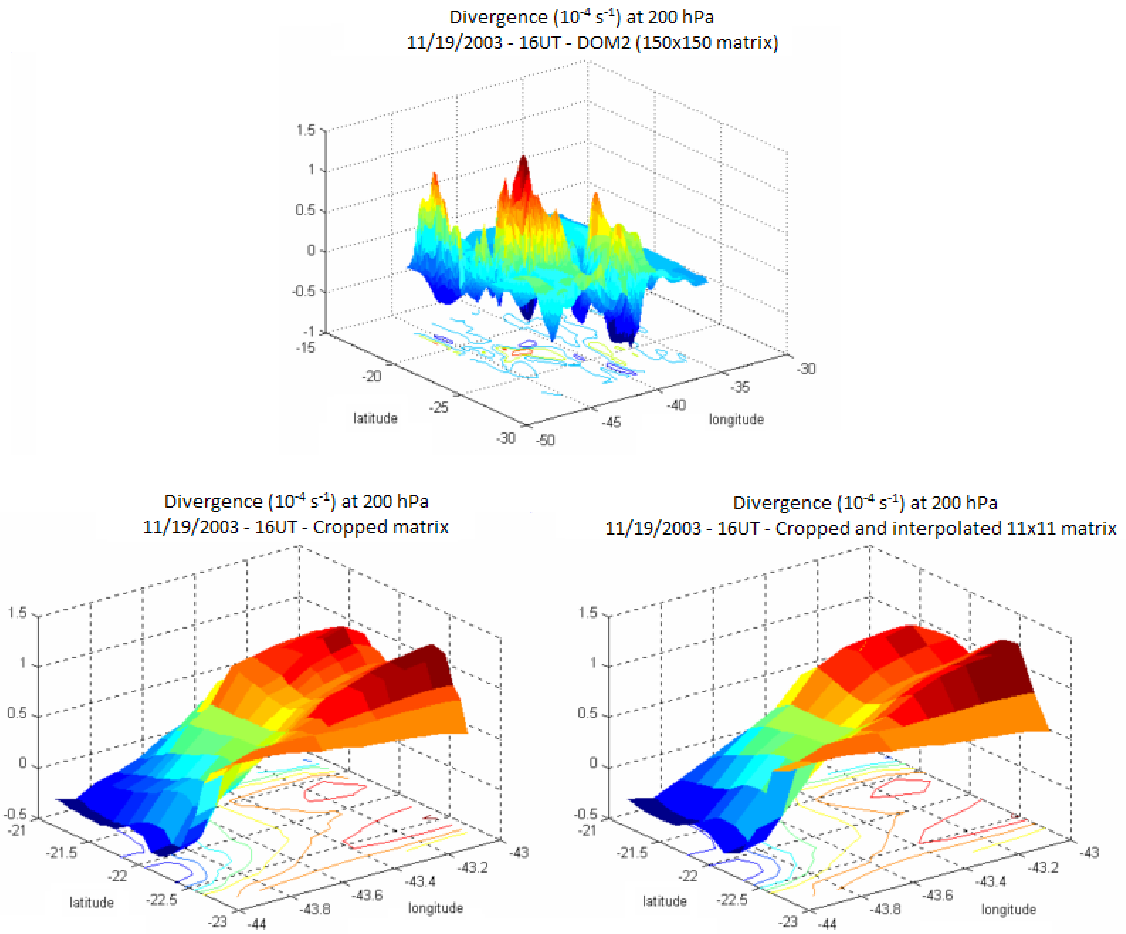

Figure 8. The procedure applied to the MM5 variables before they become the NN inputs. In this example, the 150x150 matrix of divergence at 200 hPa was converted in a 11x11 matrix according to the geographic coordinates of the lightning subregion observed in the thunderstorm occurred on November 19, 2003 at 17 UT (Figure 7).

Since the goal is the lightning forecasting at 17 UT, only the MM5 outputs of one hour before (16 UT) were analyzed. The similarities observed between both last graphs in Figure 8 indicate that no physical meaning of the MM5 variables was lost after the interpolation process.

Therefore, the configuration of neurons in the NN input layer was as follows:

• From 1 to 121 (vertical velocity at 500 hPa);
• 122 to 242 (divergence at 850 hPa);
• 243 to 363 (divergence at 200 hPa);
• 364 to 484 (water vapor-mixing ratio at surface);
• 485 to 605 (water vapor-mixing ratio at 850 hPa);
• 606 to 726 (temperature advection at 500 hPa);
• Neuron 727 corresponds to the area, in km^2, of the high-density lightning subregions.

4.2 NN Training and Results

Twenty-three high density lightning subregions were selected to compose this study. Nineteen cases were presented to the NN as training patterns, while four were left to test the efficiency of the lightning forecasting system. Table 1 shows date, hour, geographic coordinates of the subregions and total CG flashes detected. The events for testing were marked in bold and red, and, obviously, were not presented to the NN as training patterns. Three cases with no lightning were also included in the analysis, two for training the NN, and one for testing.

The NN training was performed by adopting a single iteration of the backpropagation algorithm with momentum for each case presented as training pattern. The sequence in which the cases were presented was randomly generated. After training the nineteen cases, all were also trained again with a single iteration, and so forth, until the errors reach a small limit value. Initially, the nineteen cases were presented to the NN one thousand times. Figure 9 shows the results of this training, with the red curve representing the real total flashes (patterns). The errors, calculated from the differences, after training, between NN patterns and outputs, are shown in Figure 10. The relative average error was 39.46 flashes. The NN trained with one thousand iterations was called NN1.

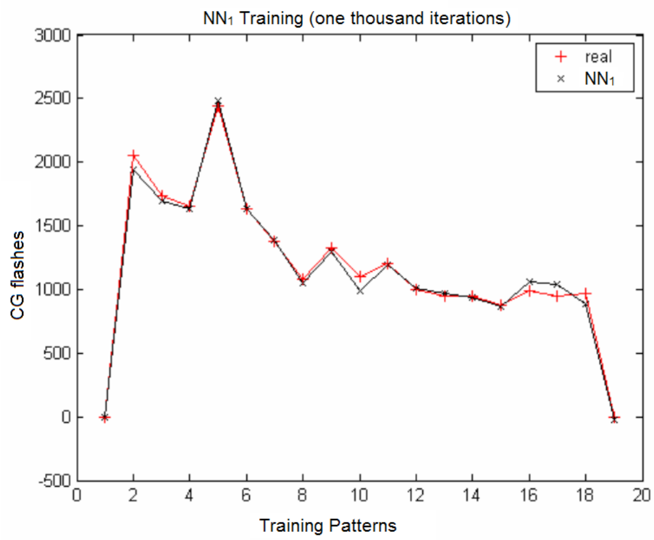

Figure 9. NN1 training. Nineteen cases of lightning subregions were used as training patterns. The real total CG flashes are indicated in red.

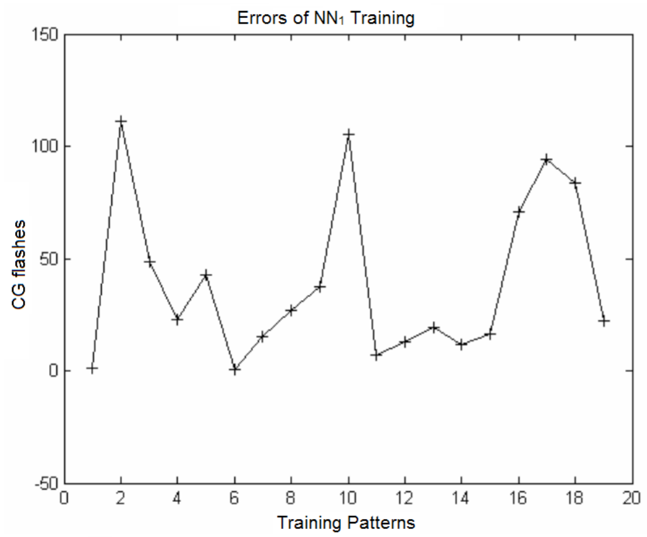

Figure 10. Errors of NN1 training (average error = 39.46 flashes).

Table 1. List of the high density lightning subregions for the NN study. The events marked in bold and red were used to test the efficiency of the lightning forecasting system.

Date	Hour (UT)	Geographic Coordinates		Total CG Flashes
		Latitude	*Longitude*	
07/05/2003	20	21°-22° S	42°-43° W	0
07/22/2003	**20**	**21°-22° S**	**42°-43° W**	**0**
09/21/2003	20	21°-22° S	42°-43° W	0
10/07/2003	22	21.3°-22.4° S	43.2°-44° W	1000
10/07/2003	23	21.4°-22.4° S	43.2°-44° W	2057
10/09/2003	03	21°-22° S	42.2°-43° W	953
11/13/2003	19	22°-23° S	43°-44° W	1378
11/13/2003	20	22.2°-23.1° S	43°-43.8° W	1741
11/13/2003	21	20.3°-21.1° S	42.8°-43.6° W	1080
11/13/2003	23	21.1°-22° S	41.9°-42.8° W	1329
11/14/2003	00	21°-22.3° S	41.4°-42.3° W	953
11/18/2003	21	20.9°-21.9° S	42.8°-43.6° W	1659
11/19/2003	20	21.2°-22.8° S	43°-44° W	2439
11/20/2003	01	21.1°-22.2° S	41.5°-42.8° W	1630
11/20/2003	02	21°-22.1° S	41.2°-42.3° W	881
11/26/2003	**19**	**20.5°-22.2° S**	**43.2°-44° W**	**1096**
11/26/2003	**22**	**22°-23° S**	**42.8°-43.6° W**	**973**
12/12/2003	**20**	**22.5°-23.3° S**	**43.2°-44° W**	**1678**
02/06/2004	22	20.8°-21.6° S	42.8°-43.6° W	994
02/06/2004	23	22.2°-23° S	43°-44° W	950
02/07/2004	00	20.2°-21° S	42.8°-43.6° W	971
02/07/2004	00	22°-22.8° S	42.7°-44° W	1097
02/07/2004	02	21.9°-22.7° S	42.3°-44° W	1202

The NN training continued until two thousand iterations, and this new NN was called NN2. Therefore, NN2 was obtained by applying one thousand iterations on NN1. Figures 11 and 12 show the results of the NN2 training and the errors, respectively. In this case, the average error was 32.56 flashes.

The four cases that did not receive training (marked in red in Table 1) were tested with both NNs. Figure 13 shows the results of the lightning forecasting with the NN1, and again the real flashes are represented by the red curve. The average error of the NN1 was 246.72 flashes. Considering the NN2, the error was 241.32 flashes, and the results are in Figure 14. There is no advantage in continuing the NN training with more iteration, since the error of NN2 was slightly lower than that of NN1, and no improvement in the phenomenon forecasting would be achieved. Table 2 describes the results of the lightning forecasting using NN1 and NN2 for each test case. Indeed the differences between the total CG flashes predicted by both NNs were not significant.

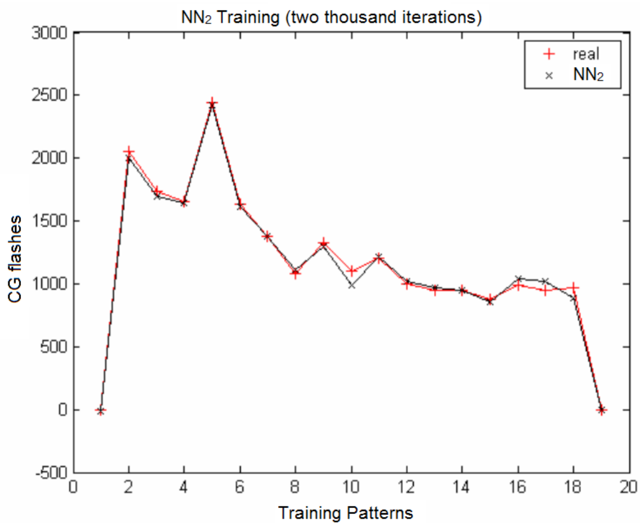

Figure 11. NN2 training. Nineteen cases of lightning subregions were used as training patterns. The real total CG flashes are indicated in red

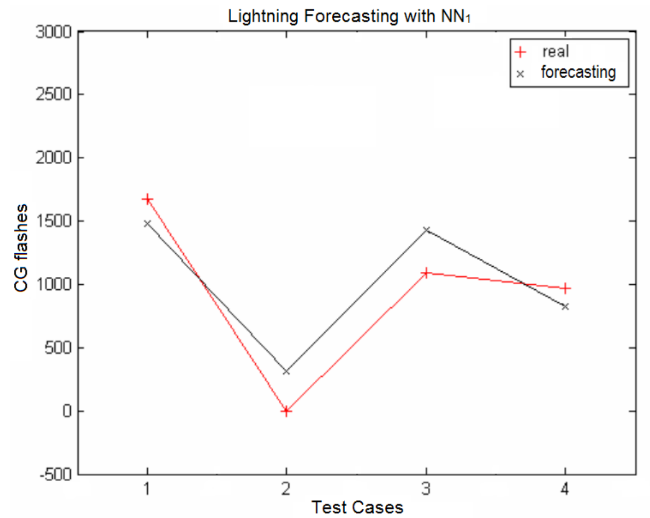

Figure 13. Results of the lightning forecasting with NN1. Four cases of lightning subregions were used to test the neural forecasting system. The real total CG flashes are indicated in red. The average error was 246.72 flashes.

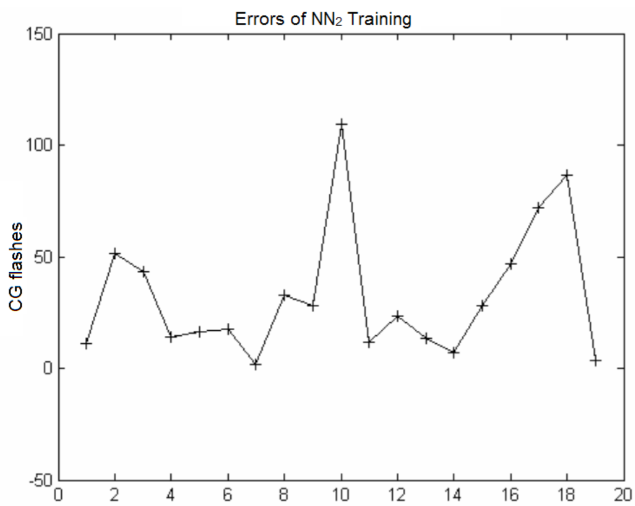

Figure 12. Errors of NN2 training (average error = 32.56 flashes).

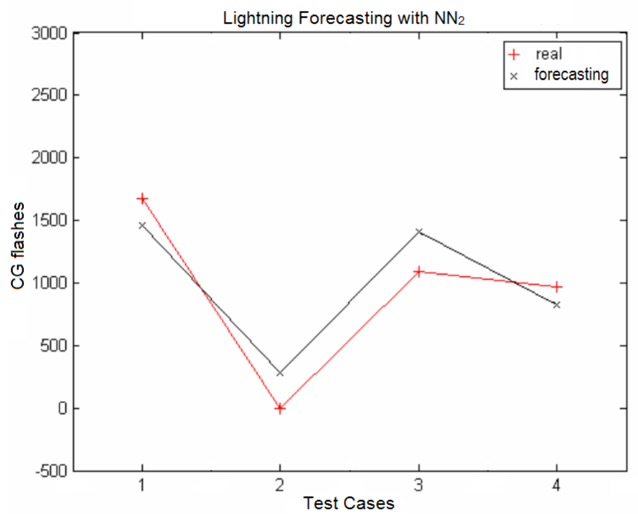

Figure 14. Results of the lightning forecasting with NN2. Four cases of lightning subregions were used to test the neural forecasting system. The real total CG flashes are indicated in red. The average error was 241.32 flashes.

Table 2. Results of lightning forecasting.

Test Cases	*Lightning Forecasting*	
Real Total CG Flashes	NN_1	NN_2
1678	1479.25	1463.36
0	308.54	282.01
1096	1426.19	1412.36
973	823.60	820.70
Training error	39.46	32.56
Forecasting error	246.72	241.32

5 Conclusions

The neural forecasting system, proposed in this work, is a combination of different MM5 variables and artificial intelligence technique to predict the lightning flash occurrence over a region of interest in southeastern Brazil. The promising results of the lightning forecasting indicated that the inputs chosen for feeding the NN correlated well with the thunderstorms activity. Four cases, not previously trained, of high density lightning subregions were used to test the system efficiency. Although the testing cases were sufficiently different, a case with no occurrence of lightning has also been included in order to not introduce any bias on the results. The average error of the NN was 241.32 flashes.

Due to the lack of studies on this subject in Brazil and the preliminary nature of this work, we decided to test the forecasting system only with one hour in advance. More detailed evaluation would be necessary to identify time intervals in which the forecasting errors remain inside acceptable limits. For this proposal, it is important to raise the NN patterns presented during the training period and the number of test cases not trained from a bigger lightning flash dataset.

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