



MINISTÉRIO DA CIÊNCIA E TECNOLOGIA
INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS

INPE-10439-RPQ/753

**EXPERIMENTS IN DATA ANALYSIS WITH NEURAL NETWORK
IN SOUTH AMERICA**

Alexandre Guirland Nowosad
Haroldo Fraga de Campos Velho
Rosangela Cintra

“A questão das forças motivadoras da expansão do capitalismo moderno não é, em primeira instância, uma questão de origem das somas de capital disponíveis para uso capitalístico, mas principalmente, do desenvolvimento do espírito do capitalismo. Onde ele aparece e é capaz de se desenvolver, ele produz seu próprio capital e seu suprimento monetário como meios para seus fins, e não o inverso”.

MAX WEBER

*To scientist
ATAIR RIOS NETO.*

ACKNOWLEDGEMENTS

The authors acknowledge the indispensable orientation of Dr. Elizabeth Silvestre Espinoza from the Division of Modeling and Development at CPTEC-INPE during this work. She explained the way to test an assimilation system should be by comparing its output to the observed data. She specified the data files from CPTEC that could be used in training and testing the neural network. She specified which atmospheric variables and which pressure levels could be used. The original idea of the first author was to test the proposed system only on 5 observation stations. She asked the system to be tested on the full 51 observation stations. Finally, after testing the neural network assimilation at one pressure level, she asked the neural network analysis to be tested at the other pressure level without retraining the net.

However, the analyses of results and conclusions of this works are exclusively of the responsibility of the authors.

H. F. de Campos Velho also acknowledges the support of CNPq-Brazil through research grant 300466/95-1.

ABSTRACT

Experiments in data analysis with a Multilayer Perceptron Neural Network (MPNN) in South America are shown. The approach used Regional Physical-space Statistical Analysis System (RPSAS) as 'reference' for training the network. Of 51 available observation stations, only data from 5 stations and at 850 mb were used to train the network. Only geopotential height at two pressure levels (850 mb and 500 mb) was analyzed. The set of examples was available for this experiment was small. Since the observation and analysis grids (RPSAS uses the grid of Eta atmosférico modelo) were not equal, the stations closest to the Eta model grid were used. The result was that analysis made by the trained network was satisfactorily close to the observed field at 850 mb.

EXPERIMENTOS EM ANÁLISE DE DADOS COM REDES NEURAIIS NA AMÉRICA DO SUL

RESUMO

Experimentos em análise de dados com uma Rede Neural de Perceptrons Multicamada (RNPM) na América do Sul são mostrados. A abordagem usou o método Regional Physical-space Statistical Analysis System (RPSAS) como ‘referência’ para treinar a rede. De 51 estações de observação disponíveis, dados de apenas 5 estações e em 850 mb foram usados para treinar a rede. Somente altura geopotencial em 2 níveis de pressão (850 mb and 500 mb) foi analisada. O conjunto de exemplos disponível para este experimento foi pequeno. Como as grades de observação e análise (o RPSAS usa a grade do modelo atmosférico Eta) não eram iguais, as estações mais perto da grade do Eta foram usadas. O resultado foi que a análise feita pela rede treinada ficou satisfatoriamente próxima do campo observado em 850 mb.

SUMMARY

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LIST OF SYMBOLS

$\vec{\mu}$ - Vector containing all biases of the neurons composing a neural network

$\vec{\theta}$ - Vector containing all weights of the neurons composing a neural network

LIST OF ACRONYMS AND ABBREVIATIONS

ANN – Artificial Neural Network

CPTEC – “Centro de Previsão do Tempo e Estudos Climáticos” (Center for Weather Prediction and Climate Studies)

Eta – A meteorological model

INPE – “Instituto Nacional de Pesquisas Espaciais” (National Institute for Space Research)

MPNN - Multilayer Peceptron Neural Network

NN - Neural network

obs - Observations

PSAS - Physical-space Statistical Analysys System

RPSAS - Regional Physical-space Statistical Analysys System

CHAPTER 1

INTRODUCTION

The data analysis process can be described as a procedure that uses observational data to improve the first guess forecast provided by an inaccurate mathematical model. For example, suppose a computational model where many properties are only expressed approximately, like turbulent fluxes. Typically, the analysis process can be outlined as a two step process:

$$\text{Forecast step: } w_n^f = F[w_{n-1}^a] \qquad \text{Analysis step: } w_n^a = w_n^f + d_n;$$

where w_n represents model state variable at n -th time step, $F[.]$ is the mathematical (forecast) model, superscripts f and a denote forecasted and analyzed values respectively, and d_n is the innovation.

Several methods of data analysis have been developed for air quality problems (Zanneti, 1990), numerical weather prediction (Daley, 1991), and numerical oceanic simulation (Bennet, 1992). In the case of atmospheric data analysis there are many deterministic and probabilistic methods (Daley, 1991; Todling, 1997). Deterministic methods include Dynamic Relaxation and Laplace Transform, whereas probabilistic methods include Optimal Interpolation, Statistical Variational Methods and Kalman Filtering. Dynamic Relaxation assumes the prediction model to be perfect, as does Laplace Transform. Statistical Variational Methods (which include Physical-space Statistical Analysis System (PSAS) and its modification Regional-PSAS (RPSAS) (Cintra, 2001) and Optimal Interpolation can be regarded as minimum-mean-square estimation of the atmosphere. In PSAS the analysis innovation d_n is computed as a linear function of the misfit between observation (denoted with superscript o) and forecast:

$$d_n = G_n (w_n^o - H_n w_n^f)$$

where G_n is a weighting (gain) matrix, w_n^o is the with error observed value of w_n and H_n is an observation matrix. Kalman Filtering uses exactly the same analysis equation as PSAS

and has the advantage of minimizing the error in the analysis plus propagating itself the error from one data insertion to the next. But it can be computationally too expensive for large systems (Mendel, 1971).

The goal of the present study was to test in a geographically limited area, namely South America, a new method proposed by Nowosad, de Campos Velho and Rios Neto to compute an assimilation function, where such function is implemented by an artificial neural network (ANN): $w_n^a = F_{ANN}(w_n^f, w_n^o)$ (Nowosad et al, 2000a,b). With this intention, a possibility of using Neural Networks for data analysis is shown. Specifically, it was the objective of this work to examine whether Multilayer Perceptron Neural Networks could improve the speed of data analysis as executed by CPTEC ('Center for Weather Prediction and Climate Studies') at INPE (National Institute for Space Research), where RPSAS is currently being used for that analysis.

RPSAS is an objective statistical system in physical space which works with more realistic links and, being a modularized system, permits introduction of non-conventional data in a relatively simple way (Cintra et al, 2001). This system is in test at CPTEC for regional atmospheric model Eta and is expected to improve significantly the predictions of this center, also allowing revision in the quality control of observations from specific regions. The analysis used in the data assimilation system is a tridimensional multi-variational Optimal Interpolation scheme; it uses structure to test advanced models of forecast and observation error covariances. PSAS differs from other optimum interpolation methods in the way it solves the analysis equation, in the removal and approximation of local data, and in the selection of data including all observations, in the simple linear system. A block pre-conditioned conjugate-gradient algorithm is used to solve iteratively the equations of the linear system.

The assimilation system creates analyzed incremental fields of: wind components, geopotential height, water vapor mixing ratio at pressure levels; increments of sea surface pressure and wind components (only near the oceans) at the sea's surface (Cintra et al, 2001). The analyses are run in four synoptic times (00, 06, 12, 18 UTC), with observations used in time windows of 6 hours (+- 3h), centered at the analyses times. The basic configuration of PSAS consists in 2° latitude for 2.5° longitude and 14 pressure levels

(1040,1000, 850, 700, 500, 400, 300, 250, 200, 150, 100, 70, 50, 40 hPa). The last step is the interpolation of analyses increments to the system of coordinates and (pressure) levels of ETA, that is, the analysis increment d_n is interpolated to the grid of model Eta and only then added to w_n^f . This interpolation was not made in the ANN method. This creates fields of surface pressure, specific humidity, virtual temperature, zonal and meridional wind at the levels. The vertical interpolation takes priority for the geopotential height increments which are converted at the average temperature using the hydrostatic equation.

The multilayer perceptron has been applied to a wide variety of tasks in atmospheric sciences (Gardner et al, 1998). Applications include prediction of air-quality prediction and severe weather, modeling nonlinear transfer functions and classification of atmospheric circulation patterns. Neural network collocation methods have also been suggested for modeling the atmosphere (Liaqat et al, 2003).

Pragmatically, this work resulted in:

- promising evaluation of the MPNN as method for meteorologic data analysis and
- indication that there are aspects of computational (software) or even physical (hardware) implementation which can be further explored to increase the efficiency of the method.

1.1 General Outline

This work was divided in 3 more chapters, described as follows:

- *CHAPTER 2 – MULTILAYER PERCEPTRONS*: In this chapter there is a brief exposition of artificial neural networks (ANNs);
- *CHAPTER 3 - RESULTS*: Results of the analyses using MPNN are shown in this chapter.

- *CAPÍTULO 4 - CONCLUSIONS*: Conclusions and perspectives of work on the methods studied here.

CHAPTER 2

DEVELOPMENT

2.1 Multilayer Perceptrons

An artificial neural network (ANN) is an arrangement of units characterized by:

- 1) a large number of very simple neuron-like processing units;
- 2) a large number of weighted connections between the units, where the knowledge of a network is stored;
- 3) highly parallel, distributed control.

The processing element (unit) in an ANN is a linear combiner with multiple weighted inputs, followed by an activation function. There are several different architectures of ANN's, most of which directly depend on the learning strategy adopted. It is not the aim of the paper to present an overview on ANN. Instead, a brief description of the ANN used is focused: the Multilayer Perceptron with backpropagation learning (Haykin, 1994).

The Multilayer Perceptron with backpropagation learning, also called the backpropagation neural network, is a feedforward network composed of an input layer, an output layer, and a number of hidden layers for extracting high order statistics from the input data (Haykin, 1994, page 19). In order to make the network more flexible to solve nonlinear problems, the activation functions for the hidden layer are sigmoid functions.

Mathematically, a perceptron network simply maps input vectors of real values onto output vector of real values. The connections have associated weights that are adjusted during learning process, thus changing the performance of the network.

There are two distinct phases in the usage of an ANN: the training phase (learning process) and the running phase (activation of the network). In the training phase, the weights are adjusted for the best performance of the network in establishing the mapping of many input-output vector pairs. Once trained, the weights are fixed and new inputs can be presented to the network for it to compute corresponding outputs, based on what it has learned.

The training phase of a multilayer perceptron is controlled by a supervised learning algorithm, which differs from unsupervised learning. The main difference is that the latter uses only information contained in the input data, whereas the former requires both input and output (desired) data, which permits the calculation of the error of the network as the difference between the calculated output and the desired vector. Adjustment of the network's weights is conducted by backpropagating such error through the network. This adjustment is called Backpropagation Algorithm. The weight change rule is a development of the Perceptron Learning Rule. Weights are changed by an amount proportional to the error at that unit, times the output of the unit feeding into the weight. This is the essence of the so-called delta rule. The training phase in batch mode is next described in more detail.

Training in batch mode, which uses all examples at the same time, searches a set of weights θ and biases μ that minimizes the total squared error

$$e_m = \sum_{n=1}^N \left\| \bar{F}_{ANN}(\bar{X}_n, \bar{\theta}, \bar{\mu}, m) - \bar{F}(\bar{X}_n) \right\|_2$$

where N is the number of examples in the training set, \bar{X}_n is the input vector of example n , $\bar{\theta}$ and $\bar{\mu}$ are the weights and biases of the network \bar{F}_{ANN} , is the approximation and \bar{F} is the desired output value.

Initialization of weights and biases can be done by randomly choosing them or by, for example, the Nguyen-Widrow method (Nguyen et al, 1990), which is the case here. The Nguyen-Widrow method linearizes the network and finds a linear interpolation initial approximation for the desired function.

In the following algorithm y_{jn} is the input to neuron j for each example n and Δ_{in} is the gradient of the error at neuron i for example n . An adaptive backpropagation algorithm in batch mode proceeds like this (Demuth et al, 1994):

- 0) Start with learning rate η_0 , momentum constant $\alpha = 0.9$, and momentum $\alpha_0 = 0$;
- 1) Calculate outputs of network and total e_m ;
- 2) If $e_m < \varepsilon$ stop;
- 3) At iteration m the backpropagation algorithm calculates:

3.1) The error gradient of each neuron i for each example n : Δ_{in} ;

3.2) New tentative weights and biases using, for each neuron i , its inputs j and each example n

$$3.2.1) \Delta(\theta_{ij})_{ij} = \sum_n \Delta_{in} Y_{jn}$$

$$3.2.2) \Delta\theta'_{ij}(m) = \alpha_m \cdot \Delta\theta_{ij}(m-1) + (1 - \alpha_m) \cdot \eta_m \cdot \Delta(\theta_{ij})_{ij}$$

$$3.2.3) \Delta\mu'_i(m) = \alpha_m \cdot \Delta\mu_i(m-1) + (1 - \alpha_m) \cdot \eta_m^2 \cdot \left(\sum_n \Delta_{in} \right);$$

4) If $e_m > 1.04 \cdot e_{m-1}$ then $\eta_{m+1} = 0.7 \cdot \eta_m$ and $\alpha_{m+1} = 0$, go to 1;

• Else

4.1) if $e_m < e_{m-1}$ then $\eta_{m+1} = 1.05 \cdot \eta_m$ and $\alpha_{m+1} = \alpha$;

4.2) Accept tentative weights and biases $\theta_{ij} = \theta'_{ij}$ and $\mu_i = \mu'_i$

4.3) go to 1.

Step 3.2.3 of this algorithm has a modification from Demuth's making the rate of change in biases μ slower than the rate of change in weights θ , because usually $\eta < 1$. In Nowosad et al (2000b) this modification was seen to improve significantly the result.

CHAPTER 3

RESULTS

The examples available to train the neural network (NN) were selected from data which was available at CPTEC-INPE. Firstly, two kinds of files, namely forecast and analysis files, come from a database generated by an Eta/RPSAS (Espinoza, 2002a) experiment intended to test that assimilation procedure for the period of time november 1st to 30th of the year 1999. Secondly, observation data for that period of time was collected from another database.

The forecast files from Eta/RPSAS were 6-, 12-, ... , 72-hour predictions of the state of the atmosphere, starting at 0h, 6h, 12h and 18h at november 1st. They were generated by an Eta atmospheric model implemented for South America. The state of the atmosphere was described using 58 variables, for example geopotential height (or simply geopotential). The state was indexed by a three-dimensional grid, where the horizontal coordinates are longitude and latitude and the vertical coordinate is pressure level (corresponding to isobars). Longitude varied from 83° W to -25.41° E in steps of 0.399994° (144 grid steps), latitude varied from 50.200001° S to 12.60° N in steps of 0.399998° (157 grid steps) and pressure varies from 100 mb to 900 mb in steps of 50mb and above that takes the values 925 mb and 1000 mb (19 levels). The set of pressure levels used are the so-called (by meteorologists) standard levels. 27 days of forecasts were available.

The analyses files were outputs of RPSAS provided at 0 h, 6 h, 12 h , 18h each day starting also at november 1st. The structure of each file was identical to that of a forecast file, using the same three-dimensional grid, and also 27 days of analysis were available.

The observation datafile was very different. It contained measurements of some variables of the atmosphere (including geopotentials) made at 0 h and 12 h at a variety of pressure levels, including standard levels but not limited to them. Some measurements were classified as being made at significant levels. There were 51 observation stations, spread over South America, they were ordered approximately from west to east and north to south. The

observation stations were not located at the horizontal grid points of the forecasting model, so their longitudes and latitudes had to be approximated to those of the forecasts.

To train the NN using observations and the corresponding forecasts and outputs of Eta/RPSAS it was necessary to organize a series of triplets made of forecasts, observations and analyses. Only observations at 0 h and 12 h were available. In addition to that limitation many observations were damaged or unusable. Observations were considered to be invalid when

$$|w_m^a(n) - \bar{w}(n)| > 3.5 \times dev(n)$$

(Vickers and Mahrt (1997)) where:

$$\bar{w}(n) = \sum_m w_m^f(n)$$

(the spatial average of the field) and

$$dev(n) = \sqrt{\sum_m (w_m^o - w_m^o)^2}$$

The underlying hypothesis is that the analysis error is zero-mean gaussian and therefore it should lie within the interval $(-3.5\sigma, 3.5\sigma)$, σ being the standard deviation.

These observations were substituted using a method to be described ahead. Only forecasts and analyses located close to the observation stations were used. 27 days of forecasts and analyses were available. The first day only had the observation at 12 h, the last day only the observation at 0h. No data from the 3rd was usable. Most of the other days had observations available as mentioned. The forecasts used were six-hour predictions starting at 18 h and 0 h. The forecast files for 2nd, 8th, 11th and 26th at 0 h were damaged so in their place the average value of the geopotential field that day was used. Finally, the missing observations at each instant of assimilation previously mentioned in this paragraph were substituted by the average value of all the forecasts used at that instant. RPSAS does not have to find

substitutes for missing observations because its observation grid is unstructured, it varies in space and time.

After describing the forecast, observation and analyses files that were used, one concluded that only 45 triplets (forecast, observation, analysis) could be used for training and testing the network. That number would usually be considered very low in face of the amount of elements to be learned, namely $51(\text{observation stations}) \times 58(\text{variables}) \times 19(\text{pressure levels}) = 26202$. Therefore only the geopotential measured at 5 observation stations, Alta Floresta (9.87° W, 56.10° S), Rio de Janeiro (22.82° W, 43.25° S), São Paulo-Guarulhos (23.62° W, 46.65° S), Curitiba (25.72° W, 49.17° S) and Porto Alegre (30° W, 51.18° S) at 850 mb was used in each triplet in a first experiment. The last four were classified as significant levels. The set of examples was then separated into a training set with 33 vector examples and a testing set with 12. The full set of 45 triplets were ordered by hour and day. The testing set was chosen selecting examples 1,4, 6, 11, 15, 20, 24, 28, 33, 35, 39, 43.

Mathematically speaking each element of the training set consisted in a pair of vectors composed of geopotentials w_m located at the observation stations:

$$x(n) = \begin{bmatrix} w_1^o(n) \\ \vdots \\ w_5^o(n) \\ w_1^f(n) \\ \vdots \\ w_5^f(n) \end{bmatrix}, \quad y(n) = \begin{bmatrix} w_1^a(n) \\ \vdots \\ w_5^a(n) \end{bmatrix},$$

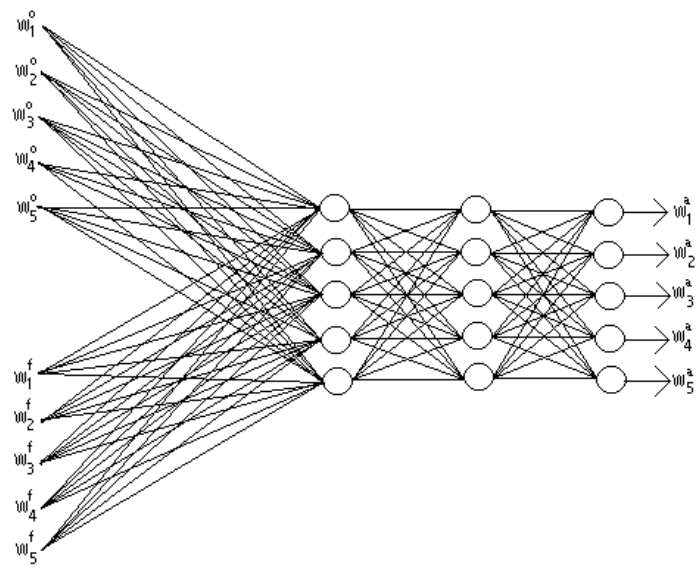
where $x(n)$ was the input pattern ($n = 1, \dots, 39$), subscript m was the number of the observation station (in the order indicated in the previous paragraph), superscript o meant observed, superscript f meant forecasted; $y(n)$ was the target output pattern and superscript a meant analyzed.

Each element of the testing set was similarly an input vector

$$z(n^l) = \begin{bmatrix} w_1^o(n^l) \\ \vdots \\ w_5^o(n^l) \\ w_1^f(n^l) \\ \vdots \\ w_5^f(n^l) \end{bmatrix},$$

where $z(n^l)$ was the input pattern ($n^l = 1, \dots, 13$).

The network had 10 inputs(one for each element of x), 5 hidden neurons and 5 output neurons. The net's architecture can be seen in figure 1. It was trained until $e_m < \varepsilon = 0.006$.



. Figure 2.1: architecture of neural network used.

The neural net thus obtained was used as a nonlinear spatial filter (a nonlinear mask)and run over the total 51 observation stations at 850 mb, from west to east and north to south, at 0h and 12 h, for each day from 1st to 27th. That meant that, starting at 12h of day 1, the forecasts and observations from each subset of 5 observations stations of the first 50 stations were fed into the input of the neural net and the corresponding analyses were read at the output of the net. For the 51st station the method had to be a little different: data from the last 5 stations were fed into the input of the net and the analysis for the last station was then read from the output of the 5th neuron. Where forecasts are missing they are substituted by the average of the geopotential field. The total RMS error (calculated including only the available observations) at instant n was then calculated using:

$$\text{RMSE}(n) = \sqrt{\sum_m (w_m^a - w_m^o)^2} .$$

This whole procedure is from now on called experiment 1. The first results obtained for NN and RPSAS (only where observations were available) are shown in figures 2, 4 and 5. In figure 3 are shown the observations. The average error of NN was expected to be at best equal to that of RPSAS, not smaller. It seems to be below 15%. NN had 21% of error at a grid point, as can be seen in figure 4. Given the small number of examples available for training, the result was considered acceptable.

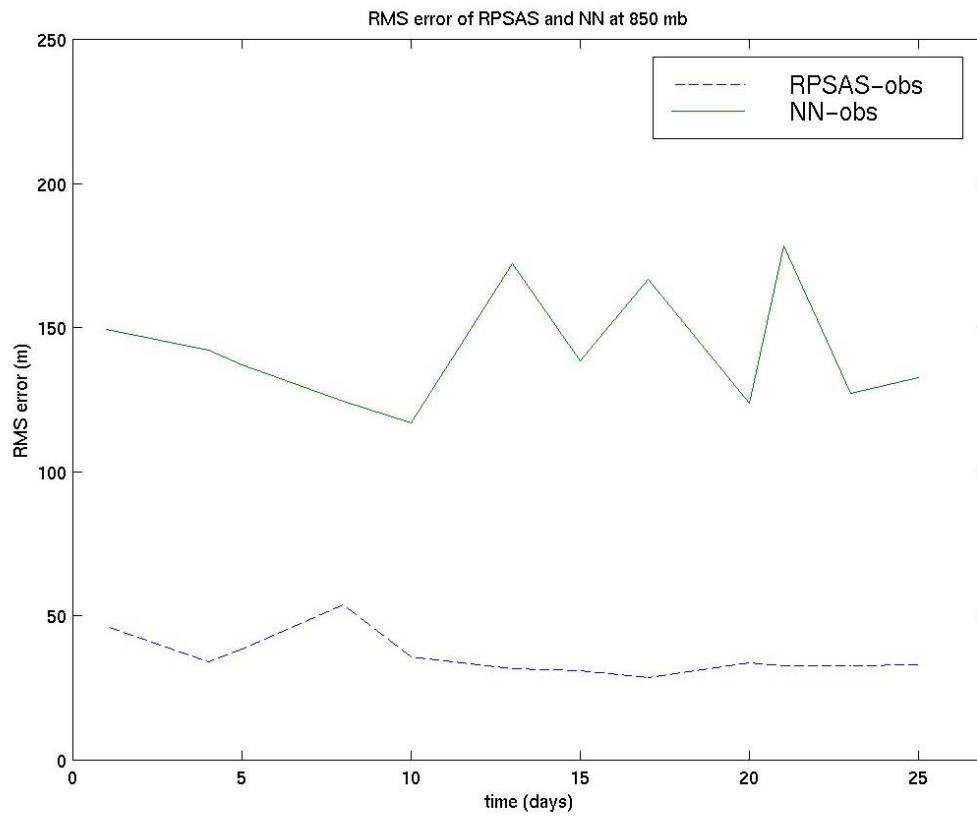


Figure 2.2: comparison between performances of Neural Net (NN-obs) and RPSAS (RPSAS-obs) in experiment 1.

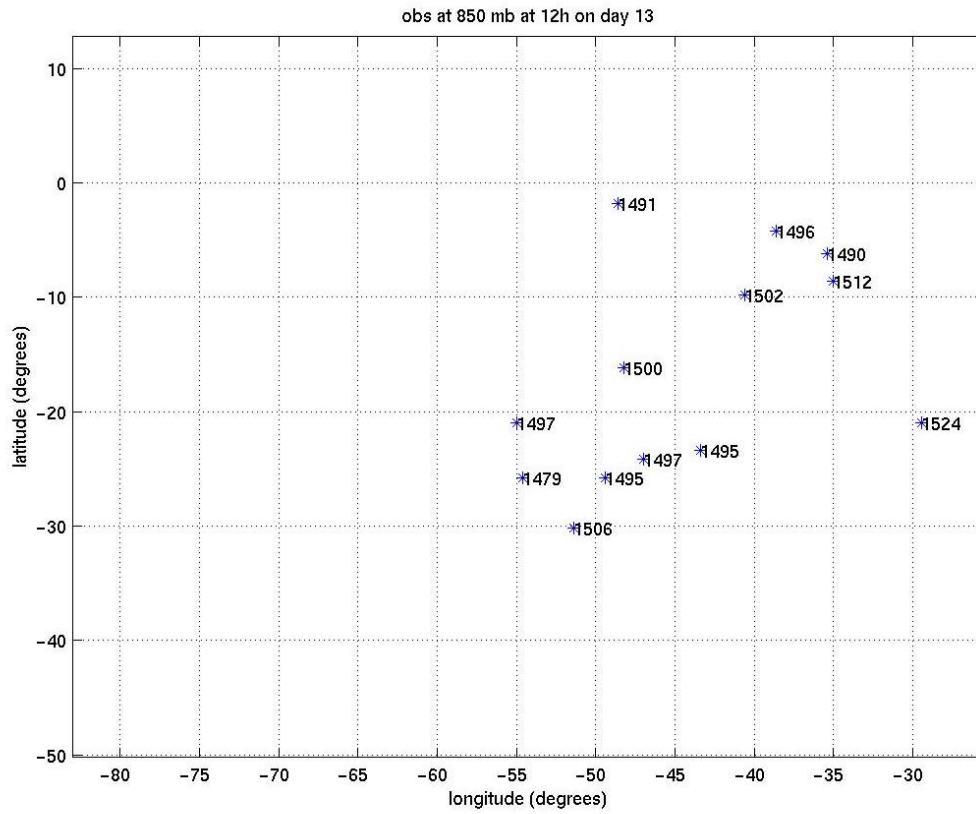


Figure 2.3: geopotential observations (obs) at a specific day of experiment 1.

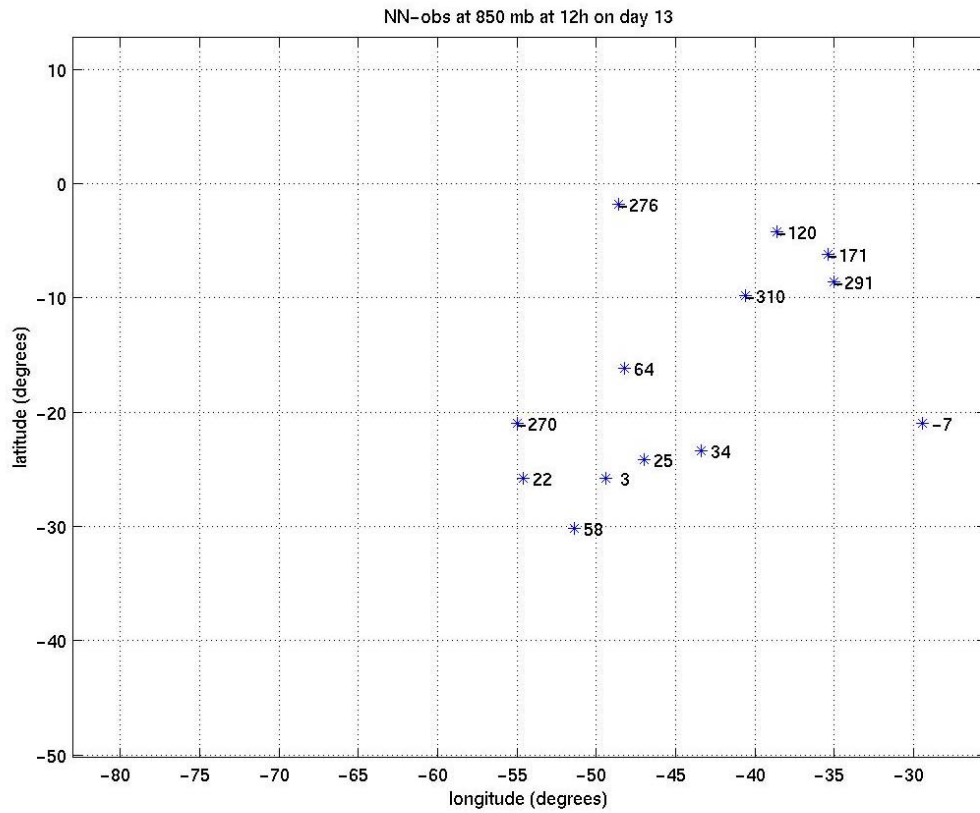


Figure 2.4: performance of Neural Net (NN-obs) at a specific day of experiment 1.

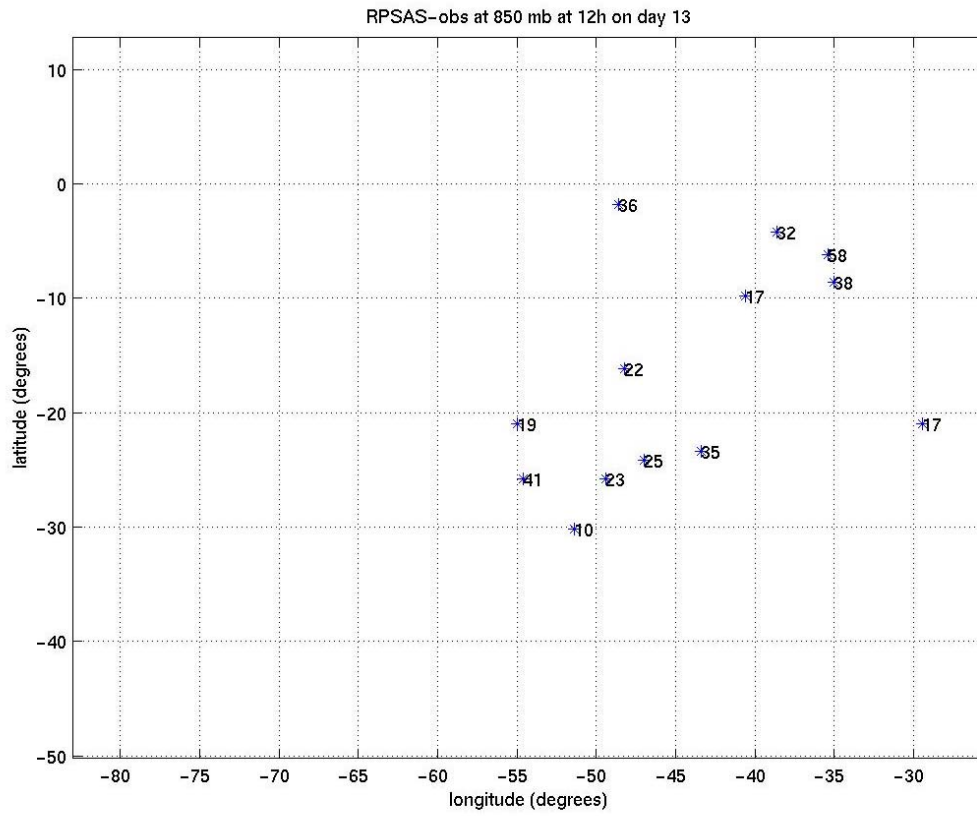


Figure 2.5: performance of RPSAS (RPSAS-obs) at a specific day of experiment 1.

Next, experiment 2 consisted in running the same mask, without retraining the neural net, over the total 51 observation stations at 500 mb, from west to east and north to south, at 0h and 12 h, for each day from 1st to 27^t. The results (at the same grid points at experiment 1) are shown in following figures 6, 8 and 9. In figure 7 are shown the observations. The average error of NN was expected to be at best equal to that of RPSAS, not smaller. It is below 13%. NN had 19% of error at the same grid point pointed out in experiment 1, as can be seen in figure 8. This result was considered unsatisfactory.

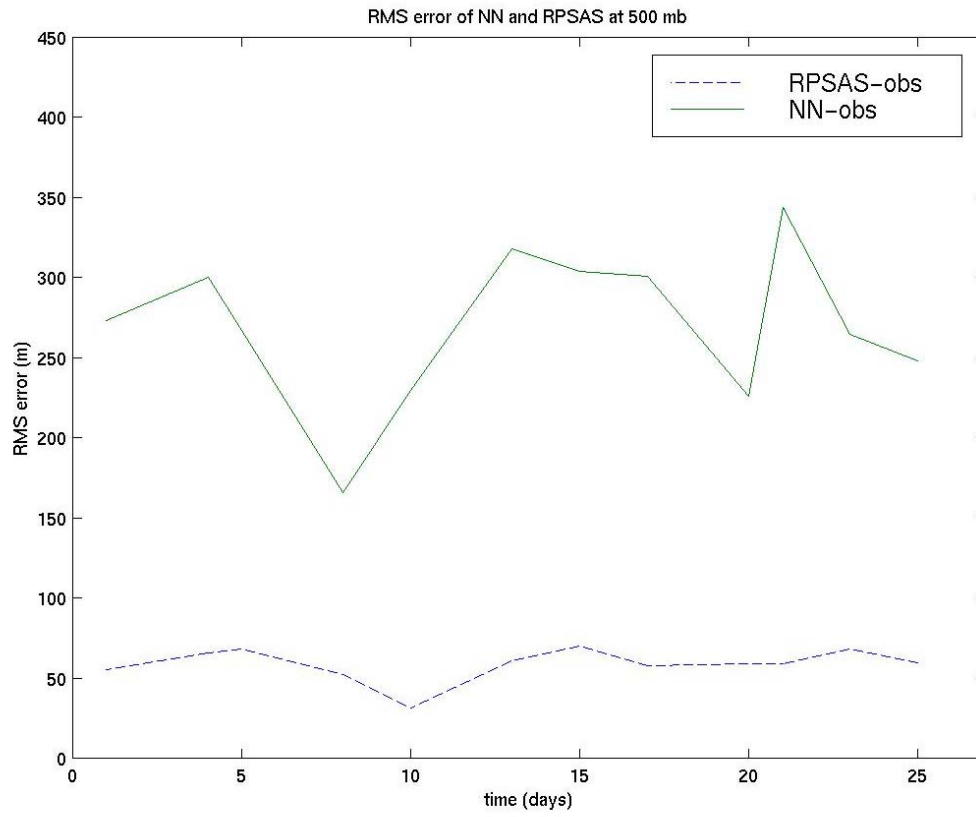


Figure 2.6: comparison between performances of Neural Net (NN-obs) and RPSAS (RPSAS-obs) in experiment 2.

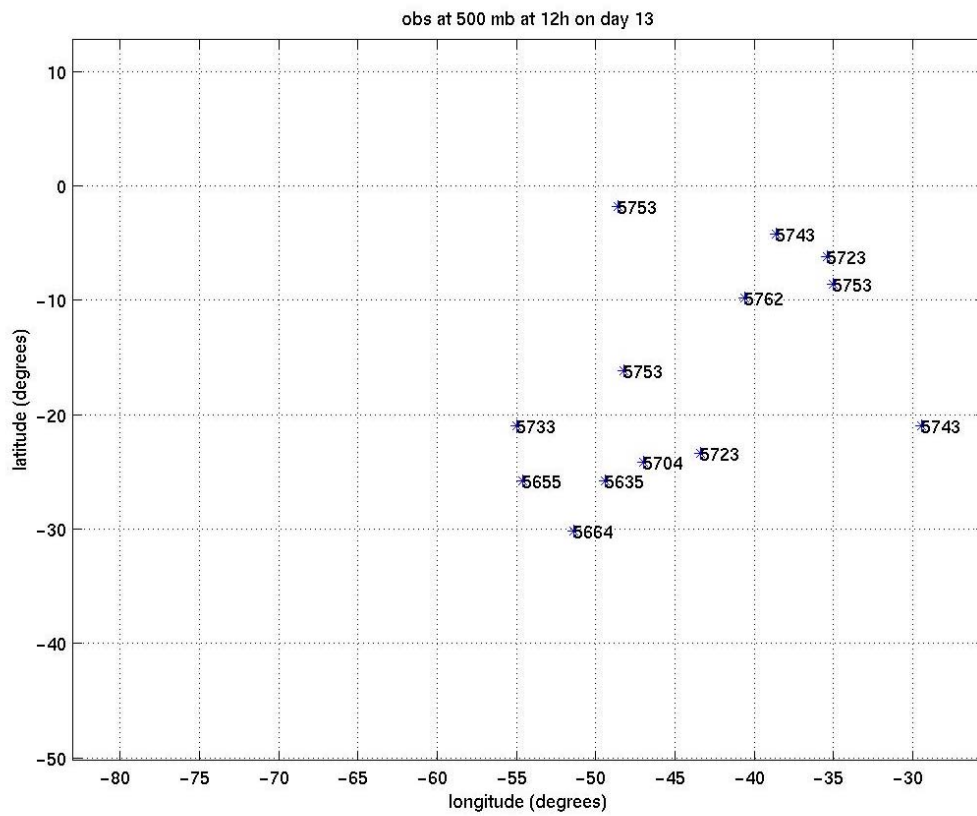


Figure 2.7: geopotential observations (obs) at a specific day of experiment 2.

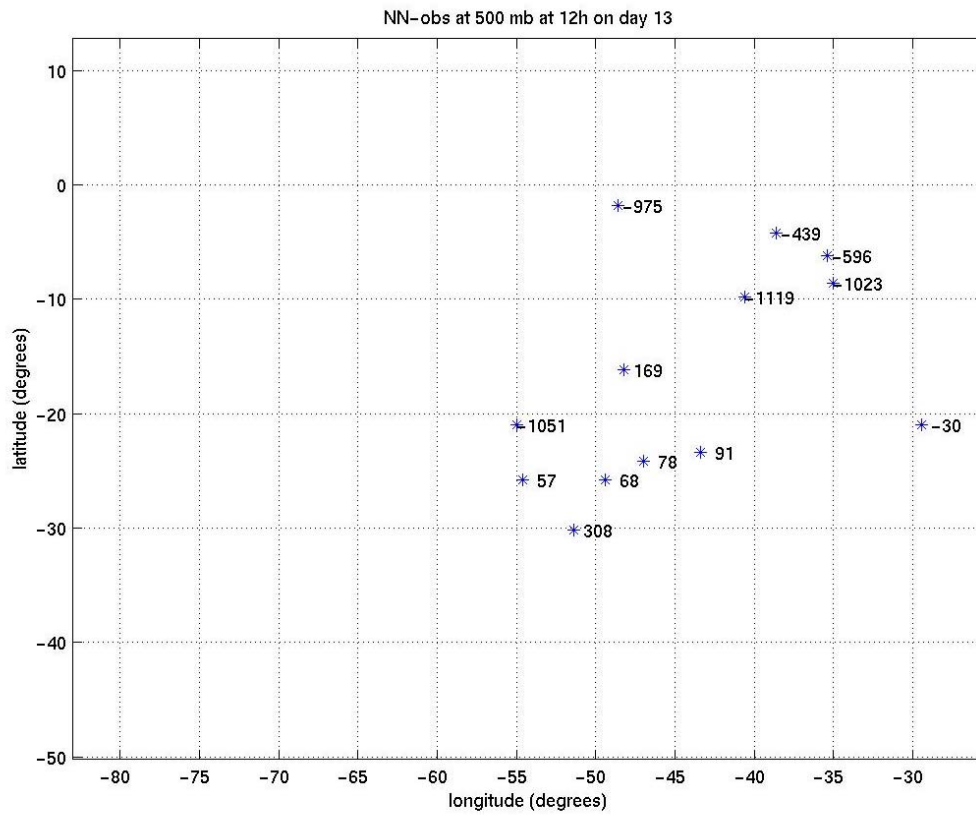


Figure 2.8: performance of Neural Net (NN-obs) at a specific day of experiment 2.

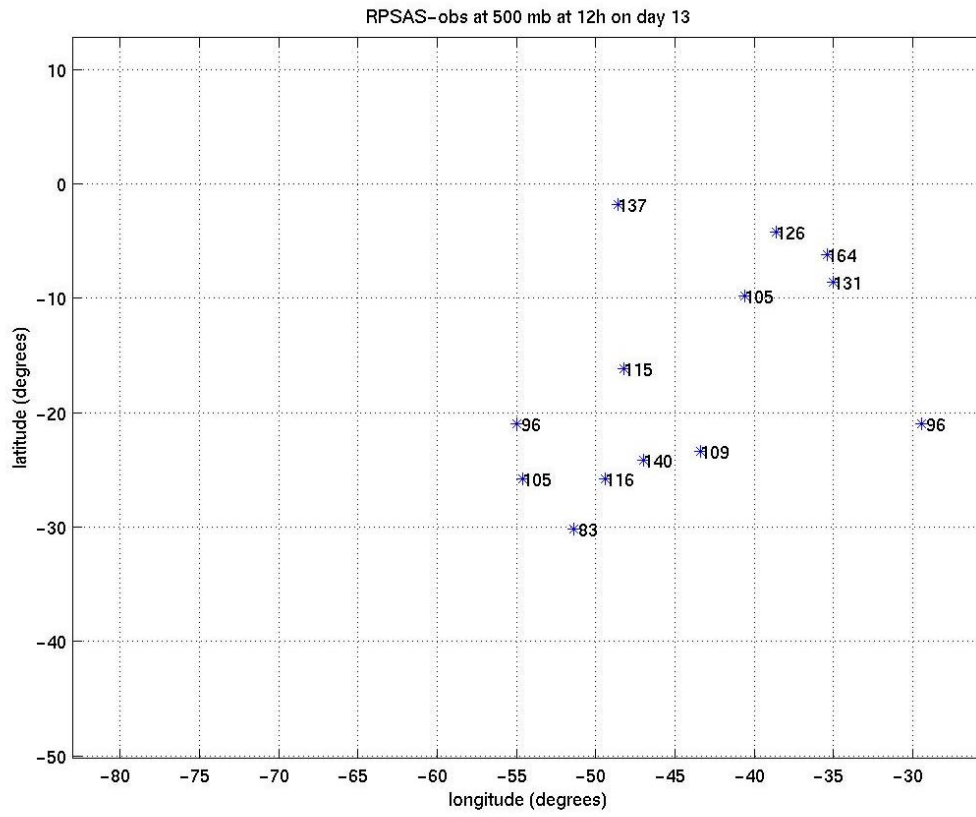


Figure 2.9: performance of RPSAS (RPSAS-obs) at a specific day of experiment 2.

CHAPTER 4

CONCLUSIONS

Experiments of geopotential data analysis with a Multilayer Perceptron Neural Network (MPNN) in South America were shown. The approach used Regional Physical-space Statistical Analysis System (RPSAS) as ‘reference’ for training the network.

Data from 45 observation stations close to Eta atmospheric model grid points for 27 days and assimilation times 0h and 12h were selected. Forecast and analysis data were selected accordingly. The amount of examples used for training was considered to be small. Therefore only geopotential heights from 5 stations and at 850 mb were used to train the network. Then analysis at two pressure levels (850 mb and 500 mb) was executed for the observation stations.

The trained network performed acceptably near the locations of the observation stations at pressure level 850 mb. *The observation grid is different from the analysis grid.* Therefore a true comparison between the performance of RPSAS and the network cannot be made. Nevertheless, the results seem to suggest that the neural network approach can be used in the future for making a data assimilation system.

Finally, the fact that such promising results were obtained training the net with the observations of only 5 stations is good news from computational point of view, allowing reduction in the algorithmic complexity of the artificial neural network.

As future work, it is intended to use the neural network trained with observational data, in which these data have been processed with a low-pass filter. This filtering process is just used to assure that non-physical information has been filtered out of the atmospheric measured data. The idea is to use an assimilation procedure simpler than Kalman filter or RPSAS in the learning phase. The use of other architectures for the neural network will also be investigated.

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