ISSN: 2229-6956 (ONLINE)
DOI: 10.21917/ijsc.2018.0243


# FOUR-LAYER SPHERICAL SELF-ORGANIZED MAPS NEURAL NETWORKS TRAINED BY RECIRCULATION TO SIMULATE PERCEPTION AND ABSTRACTION ACTIVITY - APPLICATION TO PATTERNS OF RAINFALL GLOBAL REANALYSIS

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*Abstract*

***This work is intended to organize a big set of time series. To do that a self-organized map is implemented in four spherical layers trained by recirculation. This way tries to simulate aspects of perception and abstraction. The methodology and the fundamentals are described. About the fundamentals, both from the problem point of view and the neural aspects as brain functioning, perception and abstraction concepts, psycho genetics and grouping ideas, and from the architecture of the network, scheme of training, spherical layers of the maps and algorithms involved in the iterative training. Then, it is used to organize a big set of time series of rainfall reanalysis on grid point around the Earth to show how it functions. After removing the average from the series, the annual cycle in shape and amplitude is the main criterion for organization. It is shown how the successive layers contain more general abstractions, their representativeness around the Globe and in regional scale. It is compared with individual series in some points of grid. A possible change of behaviour is found in global scale around 1973 and with a variant in the methodology a possible change in the annual cycle the same year.***

***Keywords:***

***Neural Networks, Spherical Self-Organized Maps, Recirculation, Perception, Abstraction, Psycho Genetics, Rainfall Reanalysis, Climate Variability***

## 1. INTRODUCTION

The problem of the organization of large volumes of information is in itself complex given that it is impossible to keep orders of magnitude of hundreds or thousands or even millions of numerical data under conscious control. Design criteria organization is even more complex when it does not have objective theoretical foundations and seeks to establish an order based on the same data.

The present study seeks to explore the potential of a methodology, derived from neural networks, with new aspects in the configuration and training, applied to the climatology in the organization of reanalysis of rainfall patterns in the whole area of the terrestrial Globe.

Neural networks self-organized maps are particularly useful for dealing with these issues. The present study applies specifically to climate data, but omitting either with a superficial reading specifically weather applications, it may be useful to anyone initiated in the field of neural networks and the signal analysis.

In this work the question of modeling the operation of the cerebral cortex in the perceptual process simulation is proposed in general and also discussed certain similarities with aspects related to the psycho-genetics, especially with the approach of Piaget in terms of assimilation, accommodation and organization.

At first this study contains the problem statement, objectives of the study, heuristic and methodological foundations, the proper methodology from the basics of self-organized maps, the architecture of the proposed network, algorithms, and a synthesis of the theoretical framework.

In this context, the applied problem concerns the organization of patterns of variability of global precipitation based on numerical monthly reanalysis in the period 1948-2000 at grid points on Earth, with a resolution of half a degree on latitude and longitude. For this purpose, a self-organized spherical map in four layers of neural networks trained by recirculation is used. Spherical maps allow to solve border problems on the surface of the Earth and the four layers facilitate the organization of patterns at different levels of abstraction. Recirculation tries to simulate aspects of perception and abstraction.

This work aims to explore the methodology in both generation of synthesis of time series, classification, grouping and organization of patterns by similarity. It seeks to describe the analysis at different levels of abstraction through the four layers of the network and the structure of layers in terms of organization. It demonstrates how typical time patterns can be interpreted, its projection on the Globe, and the characterization of the annual cycle like organization criteria as dominant typical pattern after the subtraction of the average. This stage of work recognizes the basic annual cycle patterns and shows how signals characterized by the network are offered as representative of typical annual cycle patterns of time series in different parts of the world. The definition of detail is explored in different layers of the network and compared with series at grid points. In this last comparison there are notable differences with specific series but this makes possible the development of synthesis as an abstraction of typical patterns representative of a set of grid points and, therefore, a classification and organization of regional annual rainfall patterns with several degrees of abstraction.

Through a variation in the methodology a possible change in behavior of the annual rainfall cycle is found around 1973.

### 1.1 STATEMENT OF THE PROBLEM: VARIABILITY AND ORGANIZATION

The problem of variability in the behavior of the atmosphere is one of the main issues of climatology. The treatment can be from a physical perspective to explaining the dynamic variability foundations and also from techniques of numerical modeling in discrete form expressing the equations that describe the behavior of the atmosphere in accordance with different parameterization criteria. The statistical approach supports several analyses but all converge in extracting numerical data, resulting from measurements of parameters that describe some features of climate behavior, as descriptive models of the processes under study. These models can be expressed as probability distributions, but also from the perspective of the algebraic form of the functions describing signals generating processes. Significance analysis requires in addition a hypothetical model on the basis of which assess the risks of error assume valid signal detection.

This last framework proposes a set of problems such as determining the number of degrees of freedom of a given signal as an expression of a process, the separation of the signal from the noise, or the statistical evaluation of hypothesis among others. Noise can be understood as an undifferentiated set of signals that occasionally respond to physically real but non-relevant phenomena on the scale in which is proposed the problem or the available measurements; it can also be interpreted as from alterations in the data of the system and measurement process. In both cases the behavior of the noise may not be Gaussian, although the usual statistical practice assumes it as such. In spectral terms, typical scenarios correspond to the notion of “white” noise in reference to the superposition of an infinite range of frequencies, or “Gaussian” noise or “red” noise under the hypothesis of persistence in first order autoregressive models. But the non-linear dynamics of the system can also generate chaotic evolution with a behavior which, from the perspective of data, can be mistaken for a random process [1]. One of the primary issues is the preprocessing of data for the purpose of separating relevant information at each stage of analysis. It is well known that the reconstruction by means of selected principal components is available as filter noise and statistical criteria of separation of signals, but presents the problem of properly selecting the components and rely on a statistic criterion in relation to the variance.

In the work the use of neural networks with several objectives is tested. First try not to resort to theoretical statistical models such as null hypotheses. Instead it proposes that the network synthesize and organize very weak signals, many of which can hardly be treated from the statistics, not only as a problem of sensitivity, but as it should require a suitable theoretical model involving spatial and time aspects for the purpose of an analysis of significance. Not to resort to a theoretical model, the notion of statistical significance is meaningless. Instead it seeks that the strength of the conclusions rests on the convergence of results from various perspectives. Whereas the “noise”, in a broad sense, as any real or random signal that masks what is meant to analyze, intends to exercise recourse to the organization of the network under different filtering forms of known signals and make use of the same network as filter noise while training retains recurring forms through the presentation of examples.

As main objectives, it attempts to explore the potential of neural networks, in the form of self-organized maps, with new aspects in the configuration and training. This SOM will be applied to reanalysis of rainfall patterns in the whole area of the Globe due to uniform global coverage without missing data. To do this, novel implementations of self-organized maps of neural networks [2] in four spherical layers trained by recirculation will be developed. It intends to simulate aspects related with perception and abstraction.

## 2. METHODOLOGICAL FOUNDATIONS

The problem of classification, characterization and organization of signal patterns is the most analyzed and widest variety of approach in different areas of knowledge and research. The most usual treatments rely on statistical analysis. Such methodologies raise hypothesis about the behavior of some of the parameters of the involved distributions, thus underlying theoretical concepts before and outside the system under study. In techniques such as principal components analysis, the hierarchy is imposed in terms of explained variance and the characterization is forced by the requirement of orthogonal functions and eventual rotation. Harmonic analysis imposes a constraint of orthogonal functions on the basis of a definition of scalar product from harmonic functions. Many of the statistical procedures are based on the normality of the distribution of the random noise. In autoregressive models an assumption is applied on the model order, the residual variance and considerations on the history of the process. These methodologies can be used in a heuristic sense, i.e., as a tool for the detection of links and characterization of patterns, but also as a matter of statistical hypothesis testing, which requires even more theoretical developments to configure the tests. One of the objectives in the proposed approach is to decrease the number and incidence of such previous, formal and external theoretical considerations, to define typical patterns and its organization and classification.

The problem from the perspective of neural networks is addressed, i.e., from an attempt of simulate the operation of the nervous system, in particular that of the cortex of the human brain. In the present paper these techniques are applied for the purposes of classification of time series, removal of synthetic patterns as representative of groups and mainly with the aim of organizing signals, in the specific form of climate patterns. This approach seeks to simulate characterization, clustering and operations organization made by the human brain; it does not impose a requirement of orthogonal functions and few previous constraints from external or theoretical models; it is also offered as a robust and simple procedure from the point of view of the involved mathematical algorithms. The main disadvantage is that the numerical results are highly dependent on initialization and processing support, but not the conclusions relating to the synthetic patterns, groups and organization.

The field of neural networks is vast and there are many textbooks for undergraduate courses that describe them from an elementary level [3] - [6]. These texts address them in general from a technical, mathematical perspective or from the point of view of the simulation of biological and neurological processes [7]. When there are results known to a particular entry and seeks the network to fit internally to new entries on the basis of the examples that are presented, it is called a supervised network. Supervised network model of wider dissemination is the multilayer perceptron. An application of this type of network models was used by Boulanger [8] [9] together with Bayesian methods to assess general circulation models in terms of adjustment to the current climate and extrapolate the output weighted by the network to the projection of future climate in a process of global warming. Instead of supervised networks, in this paper we concentrate on a variant of the application of unsupervised auto organized maps known as “Kohonen maps”.

Since the 1980s the use of neural networks was extended to the domain of the atmosphere sciences [10]. In general applications of neural networks based on Kohonen self-organized maps focus on the objective of the classification of synoptic patterns [11], climatic zoning [12], which combines the application of self-organized maps with principal components, or classification of patterns of hydrological variables [13]. Self-organized maps have been also applied in the classification of synoptic situations in conditions of potential climate change [14]. They have also been applied to the classification of circulation patterns on the basis of data of wind on height [15], the classification of satellite images [16], classification of rainfall distributions [17] or situations conducive to the development of frost [18].

Kohonen networks are offered as a useful tool for classifying, characterizing but essentially to organize signal patterns. They simulate the process of specialization of the cortex of the brain, from a neutral state of a neural network, through the presentation of examples to the network, and set up patterns of synaptic weights progressively adapted to the presented examples. From the point of view of neurological process simulation, a self-organized Kohonen map then focuses on the objective of modeling the operation of the brain cortex. It was noted that there are regions specialized in certain types of information processing in the normal operation of the brain. What follows is intended to rescue some analogies between the functioning of the nervous system in the neural processes involved in the reception of a stimulus, transduction in a sensation, the generation of a perception and the elaboration of an abstraction.

Classification, characterization and organization can't be completely independent of a previous and external theoretical scheme. Then this treatment does not lead to a quite empirical model development but to problems relating to the validity of the criteria. In this sense the problem is addressed in terms of questioning the meaning of a group, in the mathematical sense, from the point of view of human brain operations involved and associated with the process of grouping, the definition of typical patterns and the organization of elaborate syntheses. Efforts have been made to simulate some aspects relating to abstraction and perception, the latter understood as a primary abstraction by sensory processes before receiving a stimulus [19].

Therefore, attention has been given to the way for constructing the notion of group. According to the constructivist models of intelligence, developed in the field of the genetic epistemology school, the notion of group is made jointly with the operational and reversible nature of previous action schemes. That means that as long as the activities previously associated to certain situations are internalized, they are drawn up in the manner of mental experiences whose results anticipate the consequence of an action. These mental experiences are operational on the elements to a theoretical simulation mode. These are internal experiences that concur on reversible models that fit from concrete experiences and which can be operated from the groups and different subgroups on the basis of a theoretical simulation without any physical experiences on specific elements. These operations are generalized and accelerate the process of adapting to new situations to the extent that the physical experimentation is not required to accept or discard the proposed model. But this development of reversible and operational schemes is set up on the basis of the resolution of conflicts between unidirectional perceptual intuition from schemes established previously and the prediction from the schemes internalized to the extent that the intuition is inconsistent with the actual results from experience, solving the conflict in terms of predictions based on internalized models, not reproducing the models but combining them in a process of assimilation, accommodation and internal organization. These operational and reversible internally organized schemes enable the configuration of groups with cardinality, internal order, internal operations and abstract synthesis which typify them.

The fact that the same sensation can be perceived differently by different individuals, and that different sensations can give rise to the same perception is known in the psycho experience. Behind the perceptions there are various theoretical models or abstractions that sometimes can even force a variety of perceptions from a same sensitive stimulus, whether for different individuals or for the same individual but at different times prevails one model over another (a paper used as packaging or to write), or different sensations are associated with the same abstract model (paper to write, or write over sand). That is, a perception interacts with an abstract model so that it returns a perception halfway between the feeling and the model. But in such a way that the same model is modified in terms of the dialectic game between sensation and perception (well discovering the poly functionality of paper either conditions which must submit the sand so that can write over it or general terms and conditions of any object likely to be used to write media).

This brief digression is intended to observe that the so-called "self-organized Kohonen maps" can implement features of sensation, perception and abstraction, at the same time consistent with the concepts of assimilation, accommodation, internal organization, and with an approach to the notion of operational reversible groups, classification and abstraction of typical patterns in the context of the constructivist concepts of genetic epistemology concerning the development of human intelligence. It is in this context that a methodology of organization, classification and development of synthesis of signal patterns is intended to be developed.

Even when the proposed neural network model is considered to be consistent with the neurological mechanisms operating in the human brain, it does not assume any hypothesis concerning the physiological processes involved nor it speculates about whether the criteria used fits total or partially the real processes that unfold at the organic level. It does not seek to ultimately develop a physiological model of any cerebral process but of applying a procedure for classification, characterization and organization consistent with the connectionist neural networks and simulation design of mechanisms of the nervous system that involve processes of sensation, perception and abstraction, consistent at the same time with the constructivist conceptions of intelligence.

It is clear that there are elements, conditioned by the researcher almost arbitrary criterion, i.e. the definition of distance, membership, the number of neurons involved, the number of layers, response functions, the functions of interconnection of neurons among other elements necessary for the definition of the method in which one way or another Euclidean criteria of linearity persist. It is not intended by these typical patterns and the resulting classification to be more realistic, or more reliable than those obtained by other methods, but yes, it is expected to offer a tool for organization, characterization and classification consistent with the mental processes of perception and abstraction of patterns, with results appearing somewhat innovative with respect to statistical methods or other mathematically more formal classification in regard to the characterization of climate processes, in addition to incorporating the internal organization of the self-organized maps in a natural way.

## 2.1 STIMULUS, SENSATION, PERCEPTION AND ABSTRACTION

A self-organized Kohonen map focuses on the objective of modeling the operation of the brain cortex. It has been observed that in normal brain operation there are regions that have specialized in the processing of certain types of information. Kohonen network simulates the process of specialization from a neutral state of a neural network through the presentation of examples to the network and the configuration of patterns of synaptic weights progressively adapted to the presented examples.

What follows intends to rescue some analogies between the mode of operation of the brain and the proposed neural network. The brain works in parallel and distributed throughout the nervous system. Among the functions of the nervous system sensation, perception and abstraction are as responses to stimuli. In the context of the work that is developed herein, “stimulus” means a signal expressed as a time series or sequence of numeric values. “Sensation” will be the pattern of activity resulting from external stimuli on a set of neurons in the first layer of the network expressed as signal integration in a single numeric value. The “perception” will consist of the pattern of response of the neurons in the first layer to sensation in terms of a new time series. The training of the network will allow to maximize the similarity of this sequence (perception) with the pattern of entry (stimulus). “Abstraction”, on the other hand, is related to the pattern of activity remnant and resident in the synaptic connections of internal neurons in the absence of sensation and perception, but that allows us to reconstruct an image internal to the network, stable and representative of stimuli, that is expressed numerically in the pattern of synaptic weights which produce the response of the network. Abstraction sets in this way the characterization of patterns in which individual cases are not identified but the general representative of the set of elements presented to the network and identified by the typical pattern, so it allows to classify and partially rebuild input signals operating as a filter of noise in the signal in the absence of the stimulus. Self-organized map vicinity relations establish an internal organization of patterns that are synthesized by the network that is offered as a tool for classification when established patterns projected on the original database. The perception is thus interpreted as an intermediate between the sensation and the abstraction mechanism, or also as a non-resident primary abstraction.

## 2.2 ARCHITECTURE

A typical self-organized map consists of two-dimensional net receiving input signals through a set of connections weighted through synaptic weights. A Kohonen network can be used for the purpose of classification of patterns**,** but also as a tool for typing, i.e., for the extraction of patterns in general with a filtering of components of random signal noise and variability of little relevance, highlighting features of interest in the signals in the sense of configuring an empirical model by abstraction or inductive generalization from examples. The organization of patterns is essential to the mode of operation of self-organized maps. In this respect, neighborliness between patterns characterized by the network are projected onto database as links between the groups established. In general, this organization expressed in the database meets intuitive criteria or theoretical models of the process in question, but sometimes allows to set an order or sequence processes expressed in the signal under study. For example, if the patterns are fields, the organization expresses a time evolution. This approach was used in Alessandro [20] to organize the time evolution of blocking anticyclones in southern South America and the oceans. If patterns are time-series taken in different locations, the organization allows to establish a spatial development process characterized by the series as in [21].

One of the problems of the plane two-dimensional networks lies in constraints of border that imposes a plane with lateral boundaries. This problem manifests itself more intensely if it seeks to simulate a geometry as the Earth's surface. Some spherical networks have been developed in recent years as self-organized maps (Self Organizing Maps SOM) in formats 3DSOM [22], HSOM [23] in a complex helical format, GeoSOM oriented use of Earth [24] - [27] in which the problem of the display of the clusters [28] has been raised and SSOM [29] - [31] including multiple spheres [32].

In the present work this border effect is intended to be solved through a two-dimensional network of neurons equidistant in angular terms on the surface of a sphere. The locations are defined by vectors of unit module that identify the location of the neurons in the network. This network configuration of equidistant neurons is made via the random planting of points on the surface of a sphere that was repulsive electric forces numerically simulated by way of positive charge distributed over one metal sphere. Allowed the free movement of these “charged points”, is that the system is organized in a way such that the internal electric field of the sphere is null and the “points” acquire stable equilibrium positions. Neurons in the network are finally placed in the stable angular coordinates of the “charged points” and its position is identified by the azimuth and zenith angles in the network.

Another unique aspect of the proposed method is to apply recirculation to the training of the network [33]. This procedure consists of interconnecting visible neurons by synaptic weights addressed to and from neurons visible or sensitive to the hidden or internal. Each of the hidden neurons synthesized the information received or stimulus from neurons visible by way of sensation integrated in a single parameter. A pattern of inverse synaptic weights, i.e. from hidden neurons to the visible neurons, returns a set of images by way of perceptions or primary responses to the original sensation generated from the parameter scale “sensation” and neurons synaptic weights. Among all the answers or primary perceptions, that maximum similarity to the original pattern of stimuli is set. The same direct synaptic weights projected a new internal synthesis on inner neuron that generated it as a secondary reflection from selected primary perception. The recirculation procedure is to modify the direct and inverse weights so that the parameters that define the internal image of direct sensation and the reflected perception converge to the same value, as well as the primary perception is gradually approaching the pattern presented by external stimuli. As the iteration process evolves, primary perception stabilizes becoming definitive perception, or merely perception, and the pattern of synaptic weights sets up a stable abstraction that can be used in two ways: as reference pattern for future perceptions and as stimulus to train more internal network layers without evoking the original pattern that configured the stimulus. In the original Hinton method, the internal network is smaller than the outer, but not a single neuron, so what it gets is a compression of the entry in distributed memory pattern information. Distributed memory allows the original information not to be lost completely if altering the information contained in one of the neurons, but also hinders the interpretation of patterns stored in the network. By using a single neuron as internal synthesis, the benefit of distribution is lost but instead, it leads compression to the limit thus allowing that the pattern of synaptic weights stored in this single neuron can be interpreted as a synthesis of the examples presented to the network.

## 2.3 SCHEME

The following scheme summarizes signal processing for each neuron of the proposed network. A pattern of stimuli (data) comes from an environment in which the network is immersed. Those stimuli are expressed by means of a vector ($X_0$). A set of direct weights ($W_d$) leads the stimulus from the visible or sensitive neuron that receives it to an internal neuron. The sensation is obtained as a scalar product ($Y_1=W_d \cdot X_0$) between the signal or stimulus and direct weights. From the inverse weight ($W_i$), directed from the same internal neuron to the visible layer, develops the perception ($X_2 = Y_1 W_i$) as the product of a vector by a scalar. Reflection to the visible layer is interpreted as if this primary response were part of the environment, i.e. from the scalar product with the same direct synaptic weights a second internal synthesis ($Y_3=W_d \cdot X_2$) is configured. The coefficients $Y_1$ and $Y_3$ minimize their difference assimilating the direct feeling or primary ($Y_1$) to the perceptual or secondary or internal image ($Y_3$) together with the convergence of primary perception ($X_2$) to stimulation ($X_0$).

- Environment (Stimulus $X_0$) → Visible neuron ($W_d$) → Internal neuron (Sensation $Y_1 = W_d \cdot X_0$)
- Visible neuron (Perception $X_2 = Y_1 W_i$) ← ($W_i$) Internal neuron
- Visible neuron ($W_d$) → Internal neuron (Perceptive image $Y_3 = W_d X_2$)

Thus to the presentation of successive patterns to the network by way of stimuli, different unique aspects but with similar elements that make them somehow generalizable, the network internally responds with synthesis of stimulus in terms of sensation and reflections on the internal layer as a way of perceptive response, much more realistic the more assimilate perceptions to the stimulus and direct sensation or synthesis stimulation on neurons internal converges with the synthesis of primary perception on the same internal neuron. At the same time an abstraction is configured as a stable pattern of synaptic weights on the basis of which the perceptions to different stimuli are elaborated.

- Perception ($X_2$) → Stimulus ($X_0$)
- Sensation ($Y_1$) ↔ Perceptive image ($Y_3$)

Thus the perception ($X_2$) is progressively elaborated as a network response to stimulation ($X_0$), which is similar to the pattern of inverse weights ($W_i$), which will be interpreted as abstraction, which the stimulus only differs by a factor of scale ($Y_1 = Y_3$ and $X_2 = Y_1 \cdot W_i$). That is to say, the neuronal activity imposed by the stimulus is analogous and linked through the perception to the internal activity of the network. To some extent the perception provides an isomorphism between the response to the environment and the internal abstraction in terms of neuronal activity.

The structure of perception is thus characterized by vector patterns of synaptic inverse weights ($W_i$), which return the sensation ($Y_1$ direct, $Y_3$ perceptual) as assimilation in the sense of similarity to the stimulus received at the input to the network layer to reconstruct the original signal from a single scale parameter. Among all the perceptions of the network Kohonen training selects what presents a maximum of similarity in the response. Then it specializes some neurons, located in an environment that responds with greater similarity to the input pattern, bounded by a function of neighborhood. Thus inverse synaptic weights acquire the typical form of the input signal, i.e., not the unique aspects of each signal but the most general and relevant aspects that characterizes it. Therefore, the inverse patterns contain an abstract representation of the signal's origin, where the term "abstraction" is used in the sense not to represent a signal in particular but typical, general and relevant aspects for its recognition and organization, which also persists as a property acquired by the network to the training. In this way the network configures an abstraction as a result of the process of perception; in other words, perception operates as a primary mechanism of abstraction.

At the end of the training, stimuli are again presented to the network. Applying the same definition of distance between the individual patterns of information or stimuli and elaborated perceptions from abstractions, the most similar is identified between perceptual responses to each stimulus. Thus the stimulus is linked to the neuron that represents it and gets a classification of input signals through the resulting perceptions of the network in terms of the abstractions in the synaptic weights of inner layer. These patterns of synaptic inverse weights are residents by way of abstractions and organized by vicinity.

One of the additional advantages of the network is robustness in the sense of not significantly depending on iterative adjustment functions that define the rhythm of training and the radius of the vicinity. Different functions of vicinity and learning speed have been tested but no significant or relevant variations were obtained in the findings between different tests. The characteristics of speed and vicinity functions have been, in all cases tested, decreasing monotonous character.

Among the disadvantages of the methodology, and perhaps the main one, is the strong dependence of the patterns of synaptic weights and the selection at random of examples on random initialization of the neurons on the network. These processes are conditioned by the computer system, hence the use of multiple processors and even different setups with the same system lead to numerically different results. But these differences are expressed in the neurons in the network representative of each pattern of signals, which are not manifested in the classification or in the organization. From there that processes that involve random initializations are performed using the same computer system for the purpose of facilitating the analysis always referencing the same neurons. Any repetition of the experiment on another processor, these numbers and distribution in the network may vary, but the characterization, classification and organization of patterns will be not altered in a relevant way. To establish a correlation on neurological aspects, if two people are facing the same stimulus, it cannot be claimed that the same neurons are activated in their respective brains, but still the answers are comparable and communication is possible.

## 2.4 LAYERS

Another feature of the proposed network is to be formed by four spherical layers. The outer layer of sensitive neurons transfers stimuli (original scaled time series) by way of sensation to the first layer of internal neurons. In the application to signals of global rainfall, this external layer is set up on the basis of $N_0$=18142 grid points over the surface of the Earth and stimuli are expressed as time series for each of these grid points. The first inner layer is formed on $N_1$=256 neurons arranged on a spherical network. There are no objective criteria to establish the proposed number of neurons but tests with different number of neurons, but in the same order of magnitude, offered results that were similar to those who will be presented in general terms although they differ in the resolution of detail in the classification and typing. It was opted to use powers of 2 to set the number of neurons in each layer. The problem of evaluation of the quantizing error is complex. Testing has not obtained a conclusive result with respect to the best size. In relation to the topography error, the problem of designing a specific methodology arises considering that dichotomous criteria of proximity between neurons cannot be applied on the spherical network with neurons in angular terms in place of the usual vertices of an icosahedron [34][32]. It is more important the quantity of neurons to exceed the number of degrees of freedom of the variable in study to avoid that primarily different patterns are grouped together spuriously. It was noted that some of the neurons in the first layer are representative of very few grid points over the Globe, so it is assumed that the number of degrees of freedom is less than the number of neurons in the first layer of the network.

The second layer of the network contains $N_2$=64 neurons and connects with 256 neurons in the first layer. Perceptions generated by the inverse weights associated with neurons in the first layer allow to reconstruct the signals by way of an elementary abstraction. These abstractions of the first inner layer are presented as examples to the second layer of 64 neurons being configured using the same procedure applied to the time series of entrance to the first layer, a network map that contains abstractions more general and deeper. In the same way a third layer of 16 neurons is configured and trained, receiving examples generated in the second layer of 64 neurons. Finally, a fourth layer of $N_4$=4 neurons receives stimuli as examples configured on 16 neurons of the third layer so that the fourth layer contains more general abstractions. The inner layers training procedures operate by way of organization of the abstractions in the outer layers of the network.

It is clear there are elements conditioned by the criterion almost arbitrary of researcher, for example the definition of distance, the definition of membership, the number of neurons involved, the number of layers, neuron response functions, which are the functions of interconnection of neurons among other elements necessary for the definition of the method, in which predominantly persist Euclidean linearity but also criteria could resort to other geometries. Therefore, it is not intended that typical patterns and the resulting classification and organization be more realistic or more reliable than what can get from other methodological variations, but the aim is to offer a tool for classification, characterization and organization different and flexible, consistent with the neurological processes of perception and abstraction of patterns. It is not intended to either simulate the perception and abstraction in physiological terms, but only in a mathematical context in order to be applied to empirical treatment of signals.

## 2.5 ALGORITHMS

On the basis of a sphere with $N_1$ ($N_1$=256) neurons in the first layer 500$N_1$ readings series are performed, selected randomly from a database. The first process of recirculation is made from the scalar product between a vector as input $X_0(j)$ (stimulus), selected randomly through $j$ from the $N_0$ (18142) time series or signals, and a vector also generated randomly from direct weights (input to the neuron network $i^{th}$) $W_d(i)$ different for each neuron $i$(256) of the layer. A scalar field is thus generated $Y_1(i)=W_d(i)\cdot X_0(j)$ (direct sensation) on the neurons of the network that is transformed through a hyperbolic tangent in the interval (-1,1). For each neuron $i^{th}$ the direct sensation $Y_1(i)$ generates patterns $X_2(i)$ (perception) by means of a vector of inverse weights for each neuron $W_i(i)$ from the product $X_2(i)=Y_1(i)W_i(i)$. Perception generates a second internal image in the expression $Y_3(i)=W_d(i)\cdot X_2(i)$ (secondary sensation or perceptual) through direct synaptic weights $W_d(i)$. The vectors $X_0(i)$ are compared, in terms of a Euclidean norm, with $X_2(i)$ (stimulus with perception) by selecting from the $N_0$ neurons the $i$* whose perception fits better to the stimulus received (minimum distance). Simultaneously the direct sensation is compared with the perceived sensation ($Y_1(i^*)$ with $Y_3(i^*)$) and modify the synaptic weights $W_d(i^*)$ and $W_i(i^*)$ in such a way that iteratively perception approximates to the stimulus and simultaneously the direct sensation and the perceptual converge.

Among all perceptions the one that most approaches the stimulus ($i$*) is selected. Update or iterative adjustment is not limited to the "winning" neuron $i$* but develops in an environment considering the angle between the selected neuron and all the next, and also taking into account the number of iterations ($h$) developed so far in proportion to the total ($N_{it}$). The environment ($\varphi_r$) is defined from an initial angle of value π radians, which covers the complete field in the first update, and then decreases linearly with the number of iterations up to an angle of 0.01rad, which delimits a single neuron whose synaptic weights will be updated.

$$\varphi_{r(h)} = \pi + \left(0.01 - \pi\right)\frac{h}{N_{it}} \tag{1}$$

Within this environment of radius $\varphi_r$, where this topography coefficient $\varphi_r$ expresses an angular distance, synaptic weights of the neurons that are found into an angular distance $\varphi<\varphi_r$ from the neuron $i^*$ selected are updated. It is defined as the rhythm of training according to the angle factor $R_{(\varphi,h)}=\frac{1}{\left(1+\frac{\varphi}{\varphi_r}\right)^3}$ in a way such that the rhythm of learning is set to 1 in the center of the sector, i.e. for selected neuron, and 1/8 in the periphery, being null out of update radius. On the other hand, the rhythm of training decreases with the number of iterations. The rate of initial training is adopted as 0.2 and 0.01 the final learning rhythm by assigning a linear slope given by the number of iterations.

$$\alpha_{(h)}=0.2+(0.01-0.2)\frac{h}{N_{it}} \tag{2}$$

Signals are time series (636 points in time $t$) located on a grid on the surface of the Earth with 18142 inputs ($j$). The direct weight applied to the time series from the entrance $j$ to the internal neuron $i$ is updated according to the equation

$$Wd_{ijth}=Wd_{ijth\text{-}1}+\alpha_{(h)}r_{(\varphi,h)}X2_{ijt}\,(Y1_{ij}\text{-}Y3_{ij}) \tag{3}$$

In this iterative equation $Wd_{ijth}$ is the synaptic direct weight (from the outer to inner layer) internal neuron $i$ corresponding to the input or signal $j$ in the time $t$ and the presentation of the example or iterative step $h$. The coefficient $Wd_{ijth\text{-}1}$ has the same meaning but corresponding to the previous iterative step. $r_{(\varphi,h)}$ is the learning rhythm radius dependent on the angular distance between the neuron that presents the best perception of the entrance and which is being updated in the network, and dependent also on the number of iterations or examples presented to the stage $h$ training. $\alpha_{(h)}$ is the learning rhythm dependent on the number of iterations, $X2_{ijt}$ is the value at the time $t$ of perception $X2_{(i)j}$ of the signal $j$ in the neuron $i$, $Y1_{ij}$ and $Y3_{ij}$ are the internal images in neuron $i$ from the input $X0_{(i)j}$ and perception $X2_{(i)j}$ respectively.

The equation that follows is equivalent to the previous one but for inverse weights.

$$Wi_{ijth}=Wi_{ijth\text{-}1}+\alpha(h)r(\varphi,h)Y1_{ij}(X0_{\mathrm{ijt}}\text{-}\,X2_{\mathrm{ijt}}) \tag{4}$$

In this equation $W_{dijth}$ is the reverse (from the inner to the outer layer) weight from neuron $i$ at the entrance $j$ at the time $t$ in iterative step $h$. It can be seen that, in this second equation, perception fits iteratively stimulus being the direct sensation a scale factor.

It is relevant at this point observe that the matrices $W(i,t)(j)$ are only functions of $j$ during the training process. When learning concludes, the matrix $W(i,t)$ stabilizes the pattern of synaptic weights dependent on neuron, each of which has stored a vector resulting $W_i(t)$ that typifies a set of signals.

The determination of the set of input patterns better represented by each neuron is done through a measure of Euclidean distance between input to the layer pattern $X_0(i)$ and the pattern reconstructed for each neuron layer $Y_{1i}\times W_i(i)$ by selecting as the most representative neuron whose reconstructed pattern is closer to the pattern of origin, i.e., the neuron that offers the best perception of the input stimulus.

The positions of neurons have been defined by vectors $Vm_{ijk}$ where m identifies the neuron in the azimuth and zenith angle $ij$, and $k$ runs 636 synaptic weights that link each neuron with the input pattern. As typically required between 100 and 500 iterations for each hidden neuron Kohonen network, 128000 iterations have been implemented to train the network. Training is conducted randomly selecting time series at points of grid on Earth. Thus it is expected that each series corresponding to each grid point is presented to the network between five and seven times. The neuron that responds with more similarity to the stimulus and its neighboring perception are specialized to recognize a pattern that has similar characteristics. So it gets patterns of synaptic weights as a global syntheses and original signals showing similarity with characteristic patterns are identified, which in turn are organized on the map of the network. It is relevant to observe that not all data are presented to the network during the training. Considering that the experiment "presenting a series" takes place 128000 times on 256 neurons from 18142 signals or grid points, the probability that a point is selected is worth 1/18142, whereupon it is associable to a Poisson experiment with parameter $\lambda$ = 128000/18142 = 7.055. The probability that a point is not part of any sample has a value of 0.000863, with what turns out to be 16, which is the expected value of points not presented to the network, a small number compared with the points of the grid with little or no effect on training.

The training of the second layer is developed showing random patterns of abstractions stored in the first layer and reconstructed from the inverse weight $X_2(i)=Y_1(i)W_i(i)$. Patterns $X_2(i)$ operate as signals that relate 256 neurons in the first layer as projections over 64 neurons of the second layer, which thus are specialized to recognize certain patterns $W_i(i)$ of the first. The process is performed in the same way after 500*$N_2$ iterations, where $N_2=64$ neurons in the second layer. The training of the third layer is carried out following the same procedure, showing the 64 reconstructions from abstractions that relate the second layer with the first 16 neurons of the third layer. After 500*$N_3$ = 8000 iterations, the training of the fourth layer is made showing the 16 patterns that relate the third with the second layer to the four neurons of the fourth layer through 500*$N_4$ = 2000 iterations.

The process of identification of patterns to reconstruct the series of successive layers starting from the activation of neurons that are trained in the deeper layers, which is obtained by multiplying a pattern of synaptic weights $W_i(i)$ by the corresponding coefficient $Y_1(i)$. Then it compares internal reconstructed patterns with the series of inverse synaptic weights multiplied by "coefficients of sensation" $Y$ of the outermost layers, by way of reconstruction of abstractions, until the original source of data or sensitive external layer is reached. In this process first the association patterns that link layer 4 with layer 3 were rebuilt. The four patterns $W_i(i)4$ of the layer four are multiplied by coefficients $Y_1(i)4$ to generate four patterns $Y_1(i)4W_i(i)4$ with which the 16 patterns $Y_1(i)3W_i(i)3$ of the third layer are compared, linking synaptic patterns $W_i(i)3$ of the third layer with the most similar, in terms of Euclidean distance, of the four rebuilt of the fourth layer (in what follows, the reference to the layer numbers will be in the form of text (one, two, three...), while the reference to the neurons will be in numeric format (1, 2, 3...)). The same procedure applies to set up patterns of association between layer three and layer two, between the layer two and layer one, and between layer one and the data source, which could be called the zero layer or sensitive. Thus the sixteen patterns corresponding to neurons in the third layer are identified as differentially associated with each deeper fourth layer according to a criterion of Euclidean similarity in four neurons. Neurons in the third layer are associated in the same way with the neurons of the second layer. Similarly identified neurons in the first layer, defined by their patterns $Y_1(i)1\,W_i(i)1$, as associated with the neurons of the second. Finally, patterns are associated with $W_i(i)1$ and its parameters $Y_1(i)1$ with the original data series $X_0(j)$. Thus, four large regions identified in the fourth layer of neurons as more general patterns or deeper abstractions are defined over the Globe. In turn the third, second and first layers define more delimited areas which describe in more detail the behavior of time series of data.

During the development of the methodology, different alternatives have been experimented, which are discussed briefly below, but are not exposed on the work. The use of other number of neurons and layers was applied to original series after subtracted the average of the data period. This did not lead to results essentially different from those presented while more than one hundred of neurons used in the first layer and reducing the number in inner layers were not inferior to approximately between the fifth and tenth part of the of the previous layer, cases in which the grouping of dissimilar series in essentials is forced. Criteria other than the Euclidean distance, especially the use of the information contained in the synthesis developed by the network, criterion that was shown to be potentially interesting as residual entropy was practiced but had problems of stability. The problem of initialization also introduced variations in outcomes but the initial number of neurons in the first layer more than two hundred only manifested those problems in the delimitation of the border of the geographical regions identified by the network as well as the topographic distribution of neurons. It had effects on some hardly relevant aspects in the temporal synthesis so that the resulting structure in the process always performed on a same processor of computation for the purpose of facilitating the nomenclature of network in the development of the work is retained. All the computer code was built by the author in Visual Basic 6.0. It should be noted that the application of the methodology in other computer and other network resulted in topologically different results in the internal structure of the network, but with projections on the sensitive layer, i.e., on the terrestrial Globe, comparable with those presented. These changes involved the number of neuron and rotations of the patterns of organization with slight variations in the delimitation of boundaries to the extent that the quantity of neurons was not changed. It should be noted that this is consistent with the functioning of the nervous system. The neural mapping of all perceptions and subsequent processes on the basis of input stimuli is different in each individual but is still able to communicate with other individuals on the basis of the projection of this internal mapping in terms of objects and external processes to that concern.

Organization, classification and characterization of time-series applies to the original series of rainfall in grid points after being suppressed the average in this work, then in future works it will be applied to series after subtracting the seasonal process (absolute anomalies), absolute standardized anomalies (anomalies in proportion to the standard deviation), spectra from series of absolute anomalies and partial reconstruction by means of the analysis of Fourier obtaining an organization of series reconstructed in terms of phase.

## 3. DATA AND SPECIFIC APPLICATION TO CLIMATE ANALYSIS

In this work a set of neurons will be specialized in the recognition, organization and evolution of patterns of anomalies in global precipitation reanalysis, and characterizing the geographical distribution and spatial spread of the fields annual cycles. Background information consists of 53-year reanalysis (636 monthly values between 1948 and 2000 obtained from the variable “prate” from the Internet address http://cola8.iges.org:9090/dods/rean_2d.info, June 2006, NOAA 2012). A set of 18142 patterns of inputs is used.

This variable represents the speed of precipitation in cubic meters per second. In the file data are in units SI, that is, in kg/m²s. To use more environmentally friendly units to regular use, these values were multiplied by 3600 as a scaled equivalent time to preserve the stability of the neural network process and 86400*30.45 for the purposes of having monthly totals in units comparable to mm of precipitation for analysis and presentation, so that the unit SI is adjusted on a usual scale to represent the rain accumulated monthly at each grid point. These data are considered as unprocessed by not having applied any pre-filtering technique. It is known that the precipitation is among the least trusted variables or type *C* in the reanalysis [35], almost exclusively calculated in accordance with the model physics. Anyway this reconstruction contains considerable information about the pattern of rainfall regularly covering the Globe, especially the monthly totals by integrating short-term variability in regional scale.

## 4. RESULTS

A first classification of spatial patterns is shown in Fig.1.

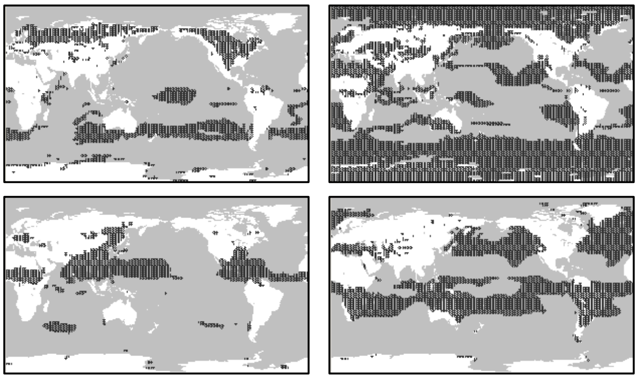

Fig.1. Global distribution of four rainfall patterns after subtraction of the average Neuron 1 above left, upper right neuron 2, neuron 3 down left and neuron 4 down right

Neuron 1 synthesizes the signal on middle and high latitudes of the northern hemisphere continental areas and oceanic middle latitudes of the southern hemisphere. It also represents a vast equatorial region in the center of the Pacific and Antarctic coastal areas. Neuron 4 expresses the complementary pattern in terms of annual cycle, covering oceanic regions in middle and high latitudes in the northern hemisphere as at the same time that continental areas of the southern hemisphere, but also tropical ocean regions. Neuron 2 identifies regions of low amplitude in the annual cycle while the neuron 3 corresponds to the maximum amplitude in this annual signal.

The Fig.2 shows the time series synthesized in the deeper layer of the network. In neuron 1 there is a maximum at the end of the 1950s and a predominance of minimum since the 1970. Neuron 2 has more stable behavior with lower amplitude. Neuron 3 rescues maximum amplitude with positive extremes at the end of the 1950s and early 1960s while minimum occur during the decades of 1980 and 1990. Neuron 4 shows intermediate and more stable amplitude than neuron 1.

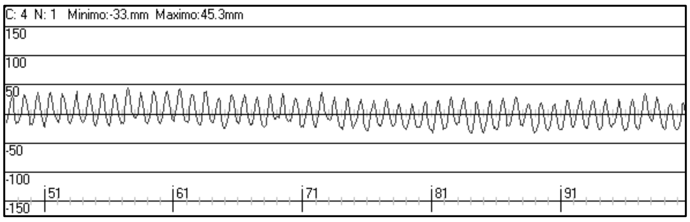


Fig.2(a). Time series corresponding to the pattern of neuron 1 of layer four

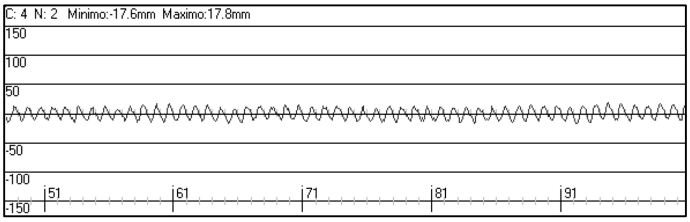


Fig.2(b). Time series corresponding to the pattern of the neuron 2 of layer four

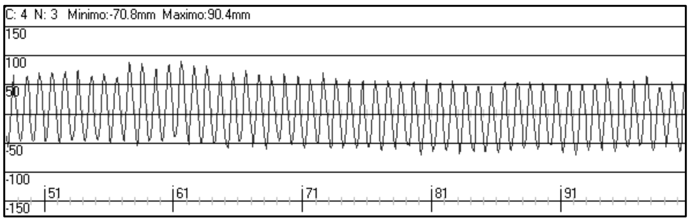


Fig.2(c). Time series corresponding to the pattern of the neuron 3 of layer four

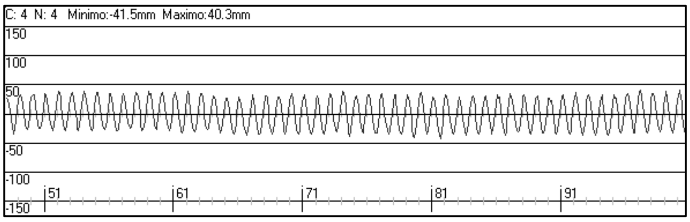


Fig.2(d). Time series corresponding to the pattern of the neuron 4 of layer four

The Fig.3 shows the form of the annual typical cycle for each of the four major reconstructions provided by the neural network. It may be noticed that neuron 1 describes a maximum in July, opposite to neuron 4, with peaks in January. Neuron 2 presents a weak yearly cycle with high between July and September while neuron 3 represents a cycle of large amplitude with maximum in July.

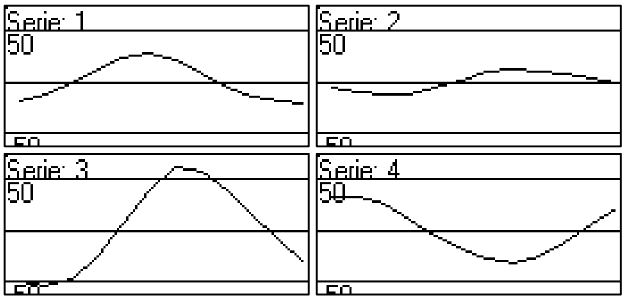


Fig.3. Annual cycle corresponding to neurons 1, 2, 3 and 4 of the fourth layer of the network

It is observed that the classification criteria adopted by the network is the form of the annual cycle of precipitation, both in amplitude and phase. The geographical distribution of the time series associated with neuron 1 corresponds to an oceanic pattern of middle latitudes of the southern hemisphere and a continental regime of middle and high latitudes of the northern hemisphere. The spatial pattern of neuron 2 corresponds to a regime of desert, this type also in polar areas, in South America dominant in Patagonia and arid areas of northern Argentina and Chile. Neuron 3 represents an annual pattern of large-scale rainfall dominant in tropical areas of the northern hemisphere, with rains in July, which extends to higher latitudes in central Europe and Eastern Asia. Neuron 4 expresses a geographical pattern with predominance in tropical regions of the southern hemisphere, with peaks in January, but also observed in oceanic regions of the northern hemisphere. Neuron 4 pattern is dominant in central and northern Argentina and southern Patagonia.

In what follows the detail provided by the reconstruction of the rainfall series from the inner layers to the outermost layers of the network will be analyzed, both in regard to the spatial as to the characteristics of the time series rebuilt. This attention will be focused on neurons that represent the behavior of rain in Argentina and especially on the Pampas Region.

The Fig.4 presents the distribution of neurons in the intermediate layers associated with four neurons in the deepest layer of the network in cylindrical projection. It can be seen how neurons in the outer layers are grouped depending on the proximity to a pattern defined by the inner layers. On the left the fourth layer with four neurons is shown represented by dots and the selected neuron surrounded by a small circle. The next column represents the third layer with sixteen neurons represented by dots and the related with the selected of the fourth layer with small circles that looks like black wider dots. The next column represents the second layer with 64 neurons and those selected related to the fourth layer neuron in wider dots. At right the first layer with 256 neurons and the related to the selected of the fourth layer encircled. The Fig.1 represents the associated neurons on the layer zero or sensitive as projected on the original time series around the Globe. It can be thought as other column of neurons on the right with the properly geographical and climatic interpretation.

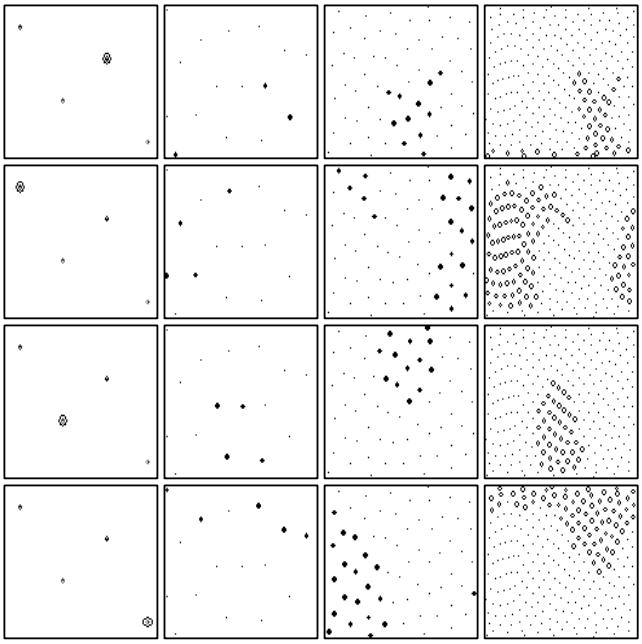

Fig.4. Layers of neurons associated with each one of the four neurons of the fourth layer. Shows selected in the fourth layer neuron and those associated in layers three, two and one from left to right in a uniform spherical distribution in cylindrical projection

The Fig.5(a) and Fig.5(b) shows the synaptic weights of neuron 14 of layer three associated with the neuron 4 of layer four. It can be seen that presents the same shape of annual cycle but more amplitude than that observed in neuron 4 of the fourth layer.

The spatial distribution of the regions represented in global scale is seen in Fig.5(c). It can be seen that it is dominant over South America south of the equator and especially on the north of the Argentine Pampas, the Argentine northeast between main rivers in Argentina and Uruguay, and the Andean Northwest.

The Fig.5(d) shows neuron 14 in layer three (circle in the top left corner of the chart) and the neurons associated with layers two and one.

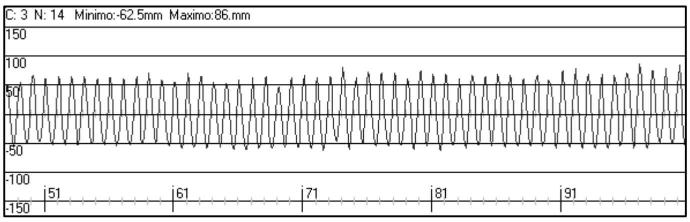


Fig.5(a). Time series corresponding to the pattern of neuron 14 of layer three

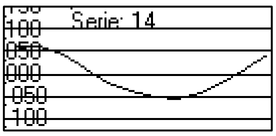


Fig.5(b). Average annual cycle corresponding to the pattern of neuron 14 of layer three

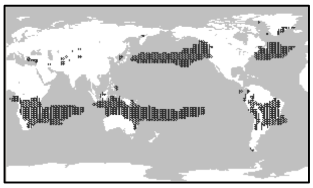

Fig.5(c). Global distribution of rainfall pattern after subtraction of the mean corresponding to the neuron 14 of layer three

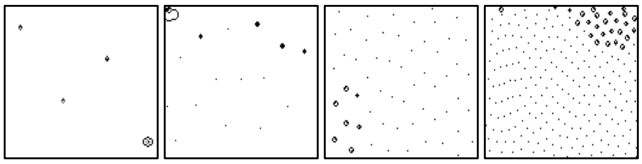

Fig.5(d). Layers of neurons associated with neuron 4 of layer four and neuron 14 of layer three. Neuron is shown in the fourth layer, the associates and the one selected in the layer three, and those associated in layer two and one from left to right in a uniform spherical distribution in cylindrical projection

Neuron 2 of layer three (Fig.6(a)-Fig.6(d)) summarizes the pattern of annual cycle of rain in the center and south of the Pampas Region. It stands out the decrease in amplitude but the preservation of annual cycle shape. It is also clear spatial neighborhood of the geographic pattern associated of neuron 2 with neuron 14, as well as the neighborhood in the neural map generated by the network.

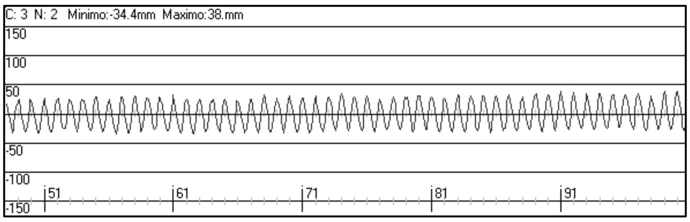


Fig.6(a). Time series corresponding to the pattern of neuron 2 of layer three

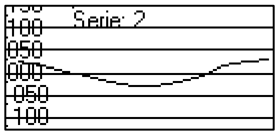


Fig.6(b). Average annual cycle corresponding to the pattern of neuron 2 of layer three

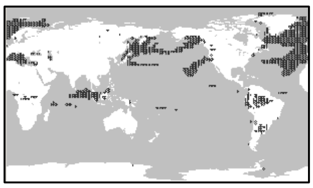

Fig.6(c). Global distribution of rainfall pattern after subtraction of the average corresponding to the neuron 2 of layer three

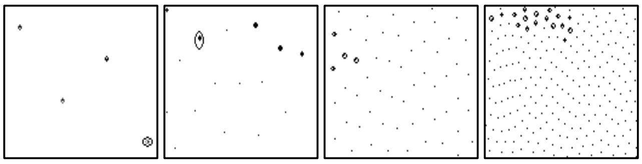

Fig.6(d). Layers of neurons associated with neuron 4 of layer four and neuron 2 of the layer three. Neuron is shown on the fourth layer, the associates and the one selected in the layer three, and those associated in layers two and one from left to right in a uniform spherical distribution in cylindrical projection

The pattern of annual cycle that synthesizes the neuron 1 of layer three (Fig.7(a)-Fig.7(d)) describes the behavior of the rain in the south of the Pampas Region and north of the Patagonia but also in the southern Patagonian. The annual cycle shape is preserved but with lower amplitude as well as the geographical vicinity and in the network map. The difference is established on a variation of low frequency in the time series that clearly shows a positive anomaly in the 1950’s and negative in the 1980.

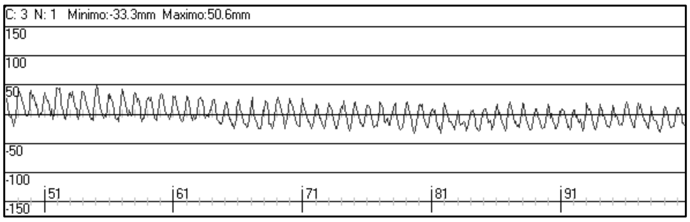


Fig.7(a). Time series corresponding to the pattern of neuron 1 of layer three

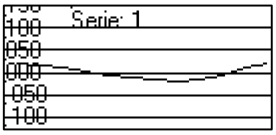


Fig.7(b). Average annual cycle corresponding to the pattern of neuron 1 of layer three

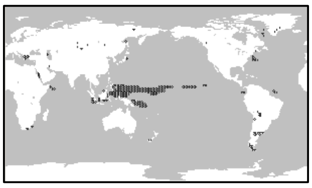

Fig.7(c). Global distribution of rainfall pattern after subtraction of the average corresponding to the neuron 1 of layer three

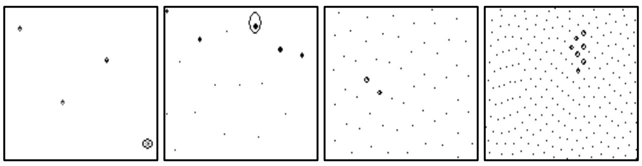

Fig.7(d). Layers of neurons associated with neuron 4 of layer four and neuron 1 of layer three. It shows neuron in the fourth layer, the associates and the one selected in the layer three, and those associated in layers two and one from left to right in a uniform spherical distribution in cylindrical projection

Neuron 8 of layer three does not have an annual cycle pattern characterizing the behavior of rain in Argentina but in the equatorial Atlantic coast of Brazil on South America, as well as other regions of the Globe, so it does not appear in the work. Instead the annual regime of a local area on the east of the Pampas and southwest of Uruguay, as well as the typical annual pattern north central Argentina and Paraguay is expressed in layer three neuron 15 (Fig.8(a)-Fig.8(d)).

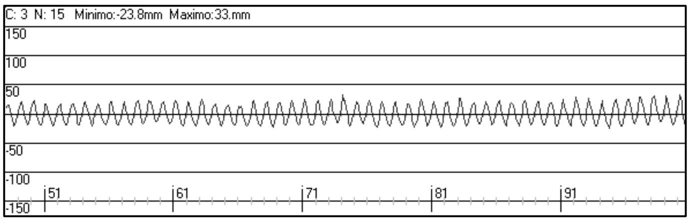


Fig.8(a). Time series corresponding to the pattern of the neuron 15 of layer three

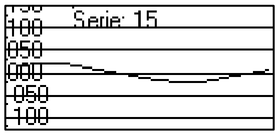


Fig.8(b). Average annual cycle corresponding to the pattern of the neuron 15 of layer three

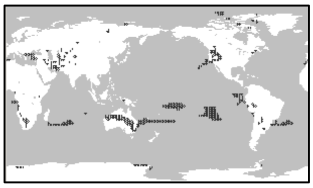

Fig.8(c). Global distribution of rainfall pattern after subtraction of the average corresponding to the neuron 15 of layer three

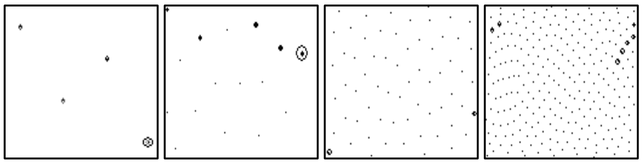

Fig.8(d). Layers of neurons associated with neuron 4 of layer four and neuron 15 of layer three. It is shown neuron in the fourth layer, the associates and the one selected in the layer three, and those associated in layers two and one from left to right in a uniform spherical distribution in cylindrical projection

It can be seen that the maximum of rainfall has moved to the months of February and March and the minimum at the end of the winter. That means that this neuron has identified a slide phase in the annual cycle.

In Fig.9(a)-Fig.9(d) it is shown that the pattern associated with the neuron 44 of layer two, linked to the layer three neuron 2, and regions of the globe with a rain pattern represented by their synaptic weights. It can be seen that this pattern corresponds to the south of the Pampas Region. It is also clear that it reflects more details in relation to the waveform and inter annual variations in the time series.

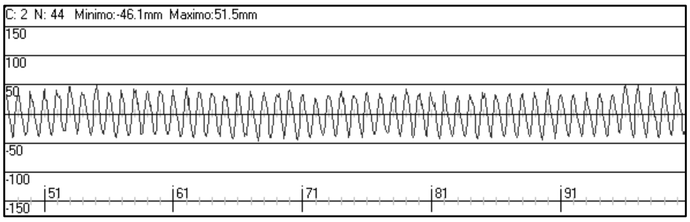


Fig.9(a). Time series corresponding to the pattern of the neuron 44 of layer two

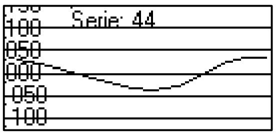


Fig.9(b). Average annual cycle corresponding to the pattern of the neuron 44 of layer two

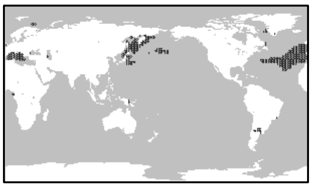

Fig.9(c). Global distribution of rainfall pattern after subtraction of the average corresponding to the neuron 44 of layer two

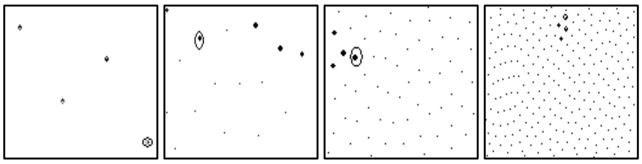

Fig.9(d). Layers of neurons associated with neuron 4 of layer four, neuron 2 of layer three and neuron 44 of layer two. It shows the neuron in the fourth layer, associated and the selected layer three, and the associated and selected in the layer two and the associated in layer one from left to right in a uniform spherical distribution in cylindrical projection

The Fig.10(a)-Fig.10(d) corresponds to the series of synaptic weights of neuron 139 in layer one. With representation more restricted almost exclusively to the south of the Pampas Region, with the exception of the similar behavior of rain in some places of the North Pacific, shows in more detail the rainfall series. The network map shows the location of the neuron 139 in the first layer.

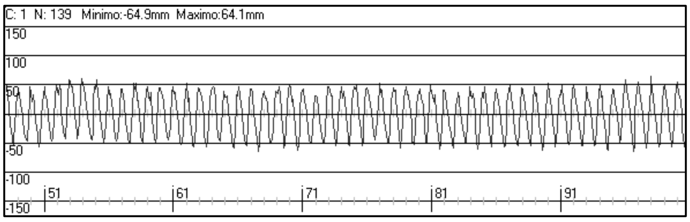


Fig.10(a). Time series corresponding to the pattern of the neuron 139 of layer one


Fig.10(b). Average annual cycle corresponding to the pattern of the neuron 139 of layer one

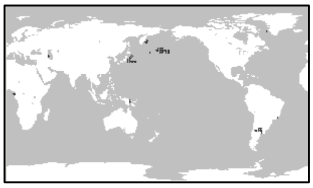

Fig.10(c). Global distribution pattern of rainfall after subtraction of the average of neuron 139 of layer one

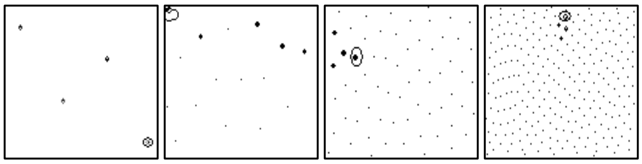

Fig.10(d). Layers of neurons associated with the neuron 4 of layer four, neuron 2 of layer three, neuron 44 of layer two and neuron 139 in layer one. It shows the selected neuron in the fourth layer, the associated and the one selected in the layer three, and the associated and selected in the layer two and the selected and associated in layer one from left to right in a spherical distribution in cylindrical projection

In order to compare the pattern defined in the synaptic weights with the individual series of precipitation, in Fig.11(a) and Fig.11(b) is observed series of reanalysis of rainfall corresponding to the grid point located at 34°S and 63°W, representative of central argentine Pampas identified by the pattern of synaptic weights of neuron 139 of layer one jointly with the associated annual waveform. It can be seen that this annual cycle has a maximum in summer and a minimum in winter with a steep slope on the behavior of the rain during the process of seasonal change.

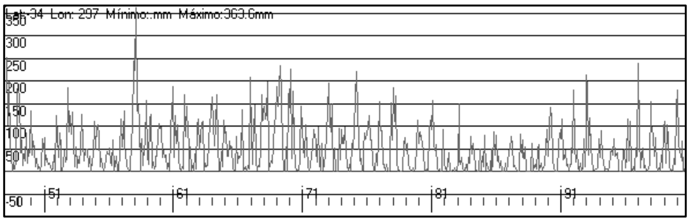


Fig.11(a). Time series of anomalies of rainfall by subtracting the average grid point represented by (-34°S; -63°O)

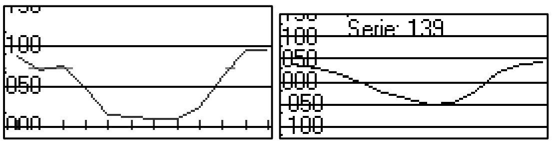


Fig.11(b). Left: Annual average rainfall cycle at the grid point represented by the coordinates (-34°S; -63°O). Right: Average associated annual cycle to the neuron 139 of the first layer of the network

The Fig.12(a) and Fig.12(b) shows the annual series of rainfall at the grid point located in -32S -60O, corresponding to the central eastern of Pampas. Both grid points are represented by neuron 139 of the first layer of the network.

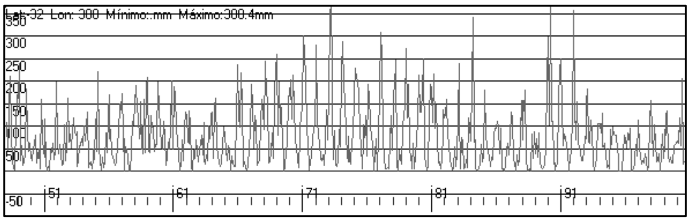

Fig.12(a). Time series of rainfall anomalies by subtracting the average at grid point represented by (-32°S; -60°O)

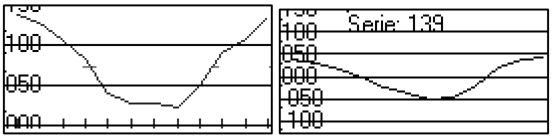


Fig.12(b). Left: Form of annual average cycle rainfall at grid point represented by the coordinates (-32°S; -60°O). Right: Average associated to the neuron 139 annual cycle of the first layer of the network

It can be seen the similarity between patterns but at the same time the difference in the rainfall regime. Neuron thus presents in its synaptic pattern of connections a typing of the annual cycle of rains in the region.

Has been calculated the annual cycle at the point of grid 57°N 166°E, east of Kamchatka, also represented by neuron 139 layer one, which displays the time series and the annual cycle Fig.13(a) and Fig.13(b) in which is observed the similarity to the seasonal behavior of the rain on the central Pampas region.

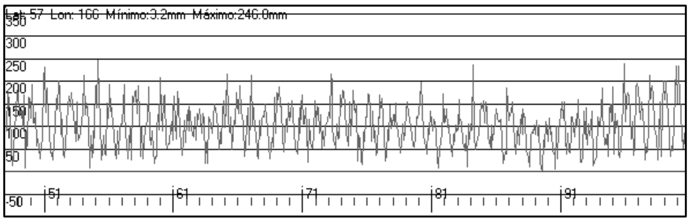

Fig.13(a). Time series of rainfall at grid point represented by (57°N, 166°E)

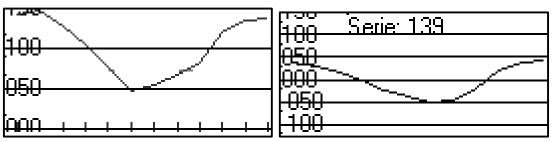


Fig.13(b). Left: Annual average rainfall wave form at the grid point represented by the coordinates (57°N, 166°E). Right: average annual cycle associated to the neuron 139 of the first layer of the network

It is clear that the process of abstraction of the network is based on local patterns at grid points to compose typical regional patterns progressively broader in terms of geographical representation and recovering the common characters of the annual cycle in the successive layers of the network. In the series of reference grid points can be seen that these contain characters defined by the resulting abstraction of the network.

A region of particular interest in relation to what will be studied in next works is located in the central equatorial Pacific. Neuron 5 of third layer (Fig.14(a)-Fig.14(d)) represents this region, along with an extensive subtropical area and east-central latitudes of the Pacific Ocean.

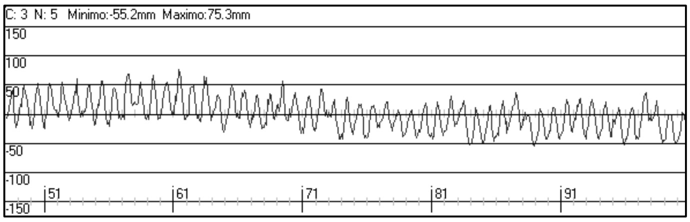


Fig.14(a). Time series corresponding to the pattern of neuron 5 of layer three after remove the average

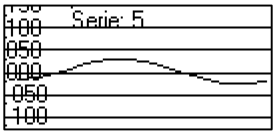


Fig.14(b). Average annual cycle corresponding to the pattern of the neuron 5 of layer three

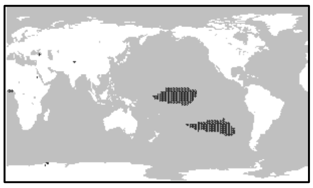

Fig.14(c). Global distribution of rainfall pattern after subtraction of the average corresponding to the neuron 5 of layer three

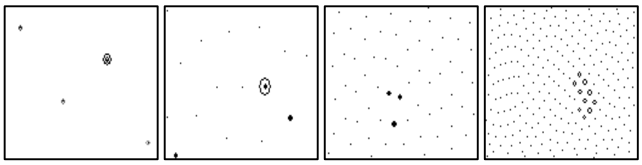

Fig.14(d). Layers of neurons associated with the neuron 1 of layer four and neuron 5 of layer three. Neuron is shown on the fourth layer, associated and the selected in layer three, and those associated in the layer two and one from left to right in a uniform spherical distribution in cylindrical projection

The annual average cycle is of modest scale with maximum in June and minimum in December but is clearly a change of long period with a noticeable decrease in the average since the beginning of the 1970s, change that appears to be from the year 1973. The neuron 54 of second layer is which detects more clearly and intensively the process of long-term change. With highs between 1957 and 1963, a decreasing trend is observed until 1973 with a posterior stabilization below the average until the end of the registration period.

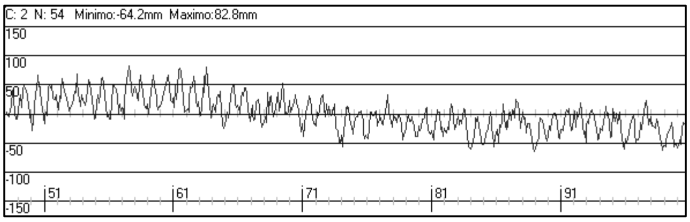


Fig.15(a). Time series corresponding to the pattern of the neuron 54 of layer two after remove the average

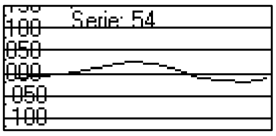


Fig.15(b). Average annual cycle corresponding to the pattern of the neuron 54 of layer two

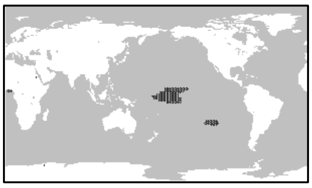

Fig.15(c). Global distribution of rainfall pattern after subtraction of the average corresponding to the neuron 54 of layer two

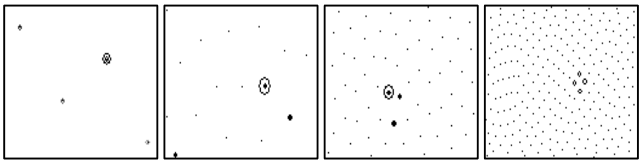

Fig.15(d). Layers of neurons associated with neuron 1 of layer four, the neuron 5 of layer three and neuron 54 of layer two. Shown neuron in the fourth layer, the associates and the one selected in the layer three, and associated and the one selected in the layer two and the associated layer one from left to right in a uniform spherical distribution in cylindrical projection

Four neurons in the first layer have this pattern of change of long period at the beginning of the 1970s, but which defines it with a maximum of amplitude and greater time expansion is neuron 207 of the first layer Fig.16. It is clear in this series the change from 1973.

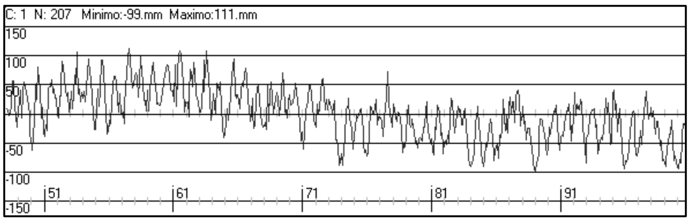


Fig.16(a). Time series corresponding to the pattern of the neuron 207 in layer one

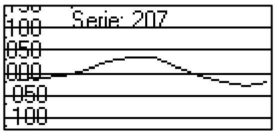


Fig.16(b). Average annual cycle corresponding to the pattern of neuron 207 in layer one

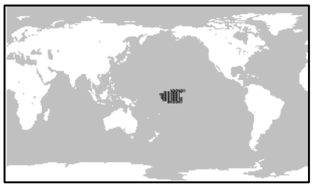

Fig.16(c). Global distribution pattern of rainfall after subtraction of the average in neuron 207 of layer one

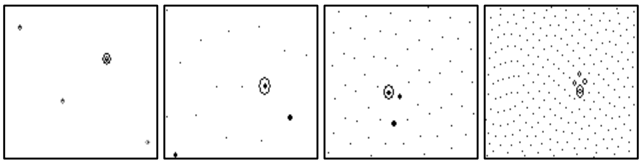

Fig.16(d). Layers of neurons associated with neuron 1 of layer four, neuron 5 of layer three, neuron 54 of layer two and neuron 207 of layer one. Neuron in the fourth layer, the associates and the one selected in the layer three, the associated and the selected in the layer two and the associated and selected in the layer one from left to right in a uniform spherical distribution in projection cylindrical

After explore the function of the network to organize annual cycle patterns and find this change of behaviour in the central Pacific around 1973, it is explored how to find changes in annual cycle through the time and just what happens in such year.

## 4.1 VARIABILITY IN ANNUAL CYCLE

This second half of the work is intended to explore how to use the network to organize main patterns of variability of annual cycle in rainfall. One of the most common problems in the study of low frequency variability is that the annual cycle is dominant in terms of variance, which hinders the study of other scales of variability, especially if statistical methods are applied. To study the weaker variability in other scales is to filter annual cycle associated with the orbital cycle by different methodologies. If the average annual cycle is subtracted from the series, it can be shown in the spectrum that part of this cycle persists in residual form. This persistence may be resulting from alterations in the average, the shape, amplitude or the phase of the annual cycle distributed during the registration period. The subtraction of the average annual cycle to study low-frequency processes would not be strictly valid if there is variability in the form of the annual cycle in the long period of time. A change in the yearly cycle would be expressing a very definite climate alteration, since annual cycle, strongly conditioned by astronomical processes, is one of the firmest and stable climatic signals. It is expected, for the same reason that these alterations are extremely weak and difficult to detect.

It has been studied the possibility of organizing a network of Kohonen in recognizing alterations in the annual wave within the same series of precipitation reanalysis. So a new network is designed consisting of four neurons with twelve entries each one. The annual rainfall series from January to December is presented by selecting random order in which the 53 years of record are shown. This neuron is able to recognize the form of the annual wave with very similar characteristics to the average annual cycle, while minor alterations are observed in each one of the four neurons although their characterization turns out to be very dependent on the random initialization conditions. For this reason, it is preferred to use the average annual cycle as a typical annual cycle to initialize the network and study the characterization of anomalies regarding this. The series of alteration in the average, shape and amplitude of the annual cycle is presented and analyzed separately from the pattern of alterations in the form of the annual cycle. Patterns of clustering in the series of 53 years may show an organized behavior realizing process of alteration of the average and/or amplitude and/or shape and/or phase in the long period.

As it was also noted that successive attempts of Kohonen mapping did not provide the same results, which allows to infer that the alterations are too small and too sensitive to initialization, this training was conducted in two stages. A pattern of annual waveform classification is obtained after two thousand iterations of a layer formed by four neurons. 240 trainings have been done with 2000 iterations each initializing neurons by recirculation with a constant value of 0.1 for the direct weights and equal to the annual cycle for inverse weights then averaging the series of synaptic weights resulting. Successive attempts show that it raises a recurring pattern of classification of the annual waveforms except some minimal differences between trainings. Training was attempted on a network of eight neurons to expand the spectrum of classification but it could be seen that in general there are one, two, but no more than three patterns of alteration clearly differentiated, by which a network of four neurons was used systematically to all the classifications of anomalies in the form of annual wave.

To show that this alteration in annual cycle is found all around the whole Earth Globe, the main pattern of rainfall stored as abstractions in the deepest layer of neuron 4 found before has been used. As can be seen in Fig.1, neuron 4 expresses the pattern, in terms of annual cycle, of oceanic regions in middle and high latitudes in the northern hemisphere and that continental areas and tropical ocean regions of the southern hemisphere. It has an opposite and greater amplitude that the neuron 1, representative of the central equatorial Pacific Ocean.

The Fig.17(a) shows the annual cycle stored in neuron 4 of layer four and the four patterns of variation found by this small net of four neurons trained in the way described above in black, red, green and blue. On the lower scale of Fig.17(b) are indicated the decades in the period 1948-2000. The top red line follows series of annual average anomalies with respect to the general average of the 53-year period. The lower series of green strokes responds to amplitudes anomalies in the annual cycle, which shows a behavior similar to the average for the period, then that the alterations in the annual average were accompanied by alterations in the amplitude of the annual cycle. The fragments in the central part of the graph show the classification of residuals annual cycles.

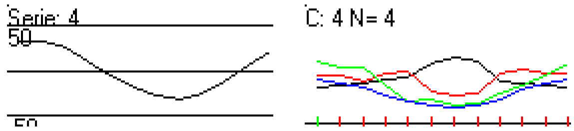


Fig.17(a). Annual cycle layer four neuron 4 and residual wave forms

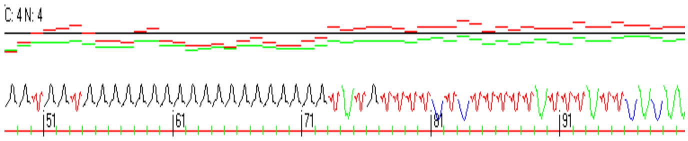


Fig.17(b). Time distribution of residual annual cycle of neuron 4 of layer four in average, amplitude and shape

The organization of annual cycles in the series summarized in the neuron 4 of layer four shows maxima around 1952, 1959, 1967, 1973, and since then a maximum in 1983 within the framework of an increase in the average of the series from 1973. It is possible that this increase is only apparent from a decade of lower rainfall during 1960, however can be seen that from 1973 all annual average precipitation values are above the average for the period of 53 years, indicated by the grey line horizontal, while before this date only the years 1951, 1952, 1953, 1958 and 1959 have values above the average. From 1973 also observed a change in the form of the annual cycle expressed through the anomaly with respect to the annual average cycle. The dominant feature until 1972 consists of a soft annual cycle, i.e., an anomaly with winter maximum and summer minimum, opposing the annual average wave-shaped. This anomaly arises again in 1976. But since 1973 the dominant anomaly is expressed as a deepening of the annual cycle with minimum in June, July and August more pronounced. Until the middle of the 1990s, dominates a minimum of anomaly in this June, July and August and a maximum during seasonal change processes. From the middle of the 1990s, and in some years during the 1970 and 1980 predominate minimum in June, July and August but peak in December, January and February. It is likely that maximum anomaly associated with the process of seasonal change, and in December, January and February have effect in an increase of the average annual rainfall.

It is noticeable that when the neuron 1 of the fourth layer shows a clear decrease in rainfall in the middle of equatorial Pacific with small amplitude in annual cycle, there is a deepening in the annual cycle around this oceanic area and others places related around the Globe, with drier winters and peaks in seasonal change, as can be seen through neuron 4 of the fourth layer.

## 5. CONCLUSIONS

The main contribution is the developing of a novel methodology on Kohonen networks. Spherical self-organized maps are proposed as a means of access to the signal analysis statistically not detectable but consistent from other perspectives such as signal analysis and validation on physical foundations. The use of spherical networks enabled solving border problems of the plane networks and settings in multilayered facilitated the organization of the information at different levels of abstraction and detail.

It has been tried to explore a way of simulating processes of perception as a primary way of abstraction. To do it, recirculation training process has been used with the main abstraction contained in the inverse weights of the neurons after training.

It has been selected almost arbitrarily the number of layers, neurons, neighborhood and training rate functions. Other alternatives should be explored but the few trials about this options give the impression of little effect on final conclusions.

This methodology can be used with all kind of series and still with only one series to explore internal similarities perhaps using lags or organizing main variable cycles into the series.

In methodological terms there are many issues open for future research. Further explore other neural network configurations and to develop criteria to systematize the dimension of the network, one of the most important issues to solve is how to preserve memory distributed in internal recirculation process synthesis. The integration of signals in a single neuron offers the benefit of the simplicity of interpretation of the resulting abstraction but is not consistent with the essential of the recirculation process approach or the operation of the cerebral cortex. In practical terms, it remains open to the exploration of other potentials of the methodology and the design of a utilitarian tool that does not require programming by the user.

In summary, it is expected to have explored a spherical variant of self-organized Kohonen maps oriented to the stratified organization of signals and their potential application to the analysis of the climate variability. The potential of the method was evaluated through the exploration of known aspects of climatology and the annual cycles of rainfall. It showed that the abstractions of the network are representative of patterns on regional scale. Interpreting the abstractions of network synthesis with spatial representativeness was shown that reanalysis on rainfall contain climatically relevant information. This is particularly useful in oceanic regions.

This work has shown how the neural network operates, how to organize the information in terms of similarity, but also in order of abstraction through four layers. It has been shown how to interpret a typical series as synthesis of regional patterns through the projection on the Globe, how to view the organization in the network and how to set base criteria for the organization, which in this application turns out to be the annual cycle.

At this stage of the work the basic annual oscillation patterns are recognized and the definition of detail and comparison with series at grid points is explored in different layers of the network. In this last comparison there are notable differences with specific series but this makes possible the development of synthesis as an abstraction of a set of grid points representing typical patterns and, therefore, a regional classification and organization of annual rainfall patterns with varying degrees of abstraction. Applying the network to the series after the subtraction of the annual average, it can be seen that is the annual cycle in shape and amplitude which prevails as a criterion for organization. Evidenced how the network can be used in the progressive selection of filtering methods and how to separate the general processes of the individual cases on the sensitive layer. To subtract the annual average, stands out as first new result and persistent in deeper levels of abstraction in the successive layers of the network, a singular pattern of variability around 1973 with their spatial distribution.

In the second part of the work a special application of a variant of the network that has been able to organize extremely weak signals has been developed. It explores the application of a single-layer spherical network with four neurons for the purposes of organizing patterns of variability in the annual cycle. From the climatological point of view, it presents a singular interest to detect a change in the pattern of annual wave of precipitation on a global scale.

The application to this organization presents serious difficulties of stability but an alteration in the annual wave is found around 1973, when, as mentioned above, there is a change in the behavior of the series in the long period. Generally speaking, in the North Atlantic, the Mediterranean, the North Pacific, the Amazonian and the equatorial Atlantic including southern Brazil and north Pampas, the eastern equatorial Pacific, south central tropical and western Pacific, Central and Northern of Australia, Indonesia, southern Africa and the Indian Ocean south of the equator is observed that the annual cycle deepens from 1973, i.e. increases in amplitude, together with an increase in average rainfall. Since 1973 a minimum of anomaly is recorded in June, July and August. Until the middle of the 1990s the maximum is observed in the process of seasonal change but since then is registered in December, January and February, which could have an impact on an increase of the average annual rainfall.

In next works related with it the methodology to series of rainfall anomalies and periodicities in spectral sign and phase shift over reanalysis on grid points of the Earth will be applied, and compared with real series rainfall related.

## ACKNOWLEDGEMENTS

I wish to thank to Universidad Tecnológica Nacional, Facultad Regional Delta, Grupo de Vibraciones Mecánicas for the support of this work, place and tools to develop it. I wish to thank to Dr. Walter Vargas for his tips and to Lic. Julio Piñeyro who introduced me into the neural networks methodology.

## REFERENCES

[1] R. Vautard and M. Ghil, “Singular Spectrum Analysis in Nonlinear Dynamics, with Applications to Paleoclimatic Time Series”, *Physica D. Nonlinear Phenomena*, Vol. 35, No. 3, pp. 395-424, 1989.

[2] T. Kohonen, “*Self Organizing Maps*”, 3rd Edition, Springer, 2001.

[3] Bonifacio Martin Del Brio and Alfredo Sanz Molina, “*Neural Networks and Blurred Systems*”, 3rd Edition, Ra-Ma Editorial, 2006.

[4] Martinez Hernando and Victor Jose, “*Artificial Neural Networks: Fundamentals, Models and Applications*”, Addison Wesley, 1995.

[5] J.A. Freeman and D.M. Skapura, “*Neural Networks Algorithms, Applications and Programming Techniques*”, Addison Wesley, 1993.

[6] Martin T. Hagan and Howard B. Mark, “*Neural Network Design*”, PWS Publishing Company, 1995.

[7] James A. Anderson, “*Redes Neuronales*”, Alfaomega Group Editor, 2007.

[8] J.P. Boulanger, F. Martinez and E.C. Segura, "Projection of Future Climate Change Conditions using IPCC Simulations, Neural Networks and Bayesian Statistics. Part 1: Temperature Mean State and Seasonal Cycle in South America", *Climate Dynamics*, Vol. 27, No. 2-3, pp. 233-259, 2006.

[9] J.P. Boulanger, F. Martinez and E.C. Segura, "Projection of Future Climate Change Conditions using IPCC Simulations, Neural Networks and Bayesian Statistics. Part 2: Precipitation Mean State and Seasonal Cycle in South America", *Climate Dynamics*, Vol. 28, No. 2-3, pp. 255-271, 2007.

[10] M.W. Gardner and S.R. Dorling, "Artificial Neural Networks (The Multilayer Perceptron) - A Review of Applications in the Atmospheric Sciences", *Atmospheric Environment*, Vol. 32, No. 14-15, pp. 2627-2636, 1998.

[11] I. Turiasa, M. Gonzalez and P. Galindoa, "A Competitive Neural Network Approach for Meteorological Situation Clustering", *Atmospheric Environment*, Vol. 40, No. 3, pp. 532-541, 2006.

[12] B.A. Malmgren and A. Winter, "Climate Zonation in Puerto Rico Based on Principal Components Analysis and an Artificial Neural Network", *Journal of Climate*, Vol. 12, pp. 977-985, 1999.

[13] M. Hall, A. Minns and A. Ashrafuzzaman, "The Application of Data Mining Techniques for the Regionalisation of Hydrological Variables", *Hydrology and Earth System Sciences*, Vol. 6, No. 4, pp. 685-694, 2002.

[14] A. Steynor and B. Hewitson, "The Use of Kohonen Self-Organising Maps in Assessing the Impact of Global Climate Change on the Runoff of the Breede River in South Africa", *Geophysical Research Abstracts*, Vol. 8, pp. 429-442, 2006.

[15] J. Fayos and C. Fayos, "Wind Data Mining by Kohonen Neural Networks", *PLoS ONE*, Vol. 2, No. 2, pp. 1-11, 2007.

[16] D. Kilpatrick and R. Williams, "Unsupervised Classification of Antarctic Satellite Imagery using Kohonen Self-Organising Feature Map", *Proceedings IEEE International Conference on Neural Networks*, pp. 32-36, 1995.

[17] S. Michaelides and C. Pattichis, "Classification of Rainfall Distributions with the use of Artificial Neural Networks", *Proceedings of 4th International Conference on Meteorology, Climatology and Atmospheric Physics*, pp. 251-256, 1998.

[18] M. Britos Cogliati and R. Garcia-Martinez, "Analysis of Agrometeorological Variables in Frost Nights using Auto Organized Maps and Induction Algorithms", Master Thesis, Department of Agrarian and Forestry Sciences, National University of La Plata, 2006.

[19] E. Kandel and T.S. Jessell, "*Neuroscience and Conduct*", Prentice Hall, 1997.

[20] P.A.A. Alessandro and D.A. Huggenberger, "Identification and Characterization of Blocking Situations through an Auto Organized Map of Neural Networks", *Proceedings of 15th Brazilian Congress of Meteorology*, pp. 13-19, 2010.

[21] Dario A. Huggenberger and Walter M. Vargas, "Evolucion De Una Oscilacion Casi Cuadrienal En La Precipitacion a Través De Un Mapa Auto Organizado De Redes Neuronales", *Acta De Trabajos Completos*, pp. 217-227, 2012.

[22] F. Boudjemai, P.B. Enberg and J.G. Postaire, "Self Organizing Spherical Map Architecture for 3D Object Modelling", *Proceedings of International Workshop on Self-Organizing Maps*, pp. 111-117, 2003.

[23] Hirokazu Nishio, Md. Altaf-Ul-Amin, Ken Kurokawa and Shigehiko Kanaya, "Spherical SOM and Arrangement of Neurons using Helix on Sphere", *IPSJ Digital Courier*, Vol. 2, pp. 133-137, 2006.

[24] Y. Wu and M. Takatsuka, "Fast Spherical Self Organizing Map-Use of Indexed Geodesic Data Structure", *Proceedings of Workshop on Self-Organizing Maps*, pp. 5-8, 2005.

[25] Y. Wu and M. Takatsuka, "Spherical Self-Organizing Map using Efficient Indexed Geodesic Data Structure", *Neural Networks*, Vol. 19, No. 6, pp. 900-910, 2006.

[26] F. Bacao, V. Lobo and M. Painho, "Geo-Self-Organizing Map (Geo-SOM) for Building and Exploring Homogeneous Regions", Available at: https://pdfs.semanticscholar.org/706a/b4e6110a3765ec0cedf2f197fe79f18c217f.pdf.

[27] F. Bacao, V. Lobo and M. Painho, "The self-Organizing Map, the Geo-SOM, and Relevant Variants for Geosciences", *Computers and Geosciences*, Vol. 31, pp. 155-163, 2005.

[28] Jorge M.L. Gorricha and Victor J.A.S. Lobo, "On the Use of Three-Dimensional Self-Organizing Maps for Visualizing Clusters in Georeferenced Data", *Proceedings of International Conference on Information Fusion and Geographic Information Systems*, pp. 61-75, 2011.

[29] A.P. Sangole and G.K Knopf, "Visualization or Randomly Ordered Numeric Data Sets using Spherical Self-Organizing Feature Maps", *Computer and Graphics*, Vol. 27, No. 6, pp. 963-976, 2003.

[30] A.P. Sangole and A. Leontitsis, "A Spherical Self-Organizing Feature Map: An Introductory Review", *International Journal of Bifurcation and Chaos*, Vol. 16, No. 11, pp. 3195-3206, 2006.

[31] A.P. Sangole and A. Leontitsis, "Estimating an Optimal Neighborhood Size in the Spherical Self-Organizing Feature Map", *International Journal of Computational Intelligence*, Vol. 18, No. 35, pp. 192-196, 2006.

[32] H. Wu, "Spherical Topology Self-Organizing Map Neuron Network for Visualization of Complex Data", Master Thesis, Department of Computing, Australian National University, 2011.

[33] G.E. Hinton and J.L. McClelland, "Learning Representation by Recirculation American Institute of Physics", *Proceedings of IEEE Conference on Neural Information Processing Systems*, pp. 358-366, 1988.

[34] E. Arsuaga Uriarte and F. Diaz Martin, "Topology Preservation in SOM", *World Academy of Science, Engineering and Technology*, Vol. 21, No. 9, pp. 991-994, 2008.

[35] E. Kalnay et al., "The NCEP/NCAR 40-Year Reanalysis Project", *American Meteorological Society*, Vol. 77, pp. 437-470, 1996.